The Performance of UK Ethical Investment Funds

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Not forgetting Tracey and Josh.

The Performance of UK Ethical Investment Funds

Abstract

The financial performance of 13 UK ethical funds is compared with market benchmarks and with the performance of sets of similar non-ethical funds. Similarly to previous research, the results suggest that ethical funds deliver a level of risk-adjusted mean financial return very similar to non-ethical funds – occasionally better, rarely worse. Unlike previous research, not only mean return but also variability is examined. A majority of the ethical funds analysed have variability about the benchmark index greater than that of similar non-ethical funds, exposing investors to increased risk for a given level of mean return. This variability is found to be less in longer-established funds (both ethical and non-ethical) so that investing with longer established ethical funds may reduce this risk relative to other ethical funds, but not relative to other similarly long established non-ethical funds. Two ethical funds, Framlington Health and Jupiter Ecology, are found to have investment objectives quite different from other ethical funds, and also to have distinct financial performance. The main novel features of this research are as follows. Firstly, a fund that was launched 'non-ethical' and later adopted ethical investment objectives is analysed, allowing investigation of the effect of this change (mean return is unaffected but variability about the benchmark index temporarily increases). Secondly, the rather restrictive way in which previous researchers have selected similar non-ethical funds for comparison has been broadened. Thirdly, the time-varying variance of returns is explicitly modelled using a full range of GARCH models; this appears to yield more reliable measures of mean performance in addition to information on variability.

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Acronyms and Abbreviations

Note: in what follows every investment fund is assigned a three-letter label; ethical funds have an asterisk appended to this

AAE	Abbey Assets & Earnings (peer to FCE*)
AAM*	Allchurches Amity A Inc (* denotes an ethical fund)
ABP	AEGON The Balanced P'folio (peer to IIE*)
ADG	Abbey Dividend & Growth (peer to ENV*)
AEG*	Aegon Ethical (* denotes an ethical fund)
AEI	Aberdeen Equity Income (peer to FPS*)
AGG	Artemis Global Growth (peer to CFE*)
AIC	Akaike Information Criterion
ARCH	autoregressive conditional heteroscedasticity
ATT	AEGON Technology Tactical (peer to FRA*)
AUE	AEGON UK Equity Income (peer to AAM*, SET*)
AUG	Aberdeen UK Growth (peer to ISG*)
AXA	AXA Global Growth (peer to JUP*, ENV*)
BGI	BGI Smaller Cos (peer to SWE*)
BIE	Bank of Ireland Exempt Equity Value (peer to AAM*, SET*)
BIW	Bank of Ireland Worldwide Opps (peer to CFE*)
CAPM	capital asset pricing model; variations on this are commonly used to assess portfolio performance
CFE*	City Financial Ethical (Acorn) (* denotes an ethical fund)

CFS	CF Stewart Ivory Investment Market (peer to IIE*)
CGARCH	Component GARCH
CSA	Credit Suisse Alpha Growth Retail (peer to SWE*, AEG*)
CSM	Credit Suisse Monthly Income (peer to ENV*)
CUO	Cazenove UK Opportunities (peer to JUP*, AEG*, SET*)
CUT	Consistent Unit Trust (peer to AAM*, SET*)
DGS	Deutsche GlobalSpectrum UK (peer to FPS*, AEG*, SET*, ENV*)
DUK	DWS UK Equity Income (peer to SWE*)
Eiris	UK Ethical Investment Research Service
EGARCH	Exponential GARCH
EGO	Exeter Global Opportunities (peer to IIE*)
ENV*	CIS Environ (* denotes an ethical fund)
Eurosif	European Social Investment Forum
FAM	Family Asset (peer to AEG*)
FCE*	Family Charities Ethical fund (* denotes an ethical fund)
FIV	Five Arrows GI UK Major Cos (peer to SWE*)
FLE	Fleming PIC Gth 2000 (peer to SWE*, FPS*, AAM*, AEG*, SET*)
FPI	Friends Prov Int'l Growth (peer to FRA*)
FPS*	Friends Prov Stdship Income (* denotes an ethical fund)
FRA*	Framlington Health (* denotes an ethical fund)
GAM	GAM UK Diversified (peer to AEG*, SET*)
GARCH	generalised auto-regressive conditional heteroscedasticity

GARCH-M	GARCH-in-mean i.e. a GARCH term is included in the mean equation
GME	Gartmore PS Managed Eq (peer to IIE*)
HAC	Heteroscedasticity-and-Autocorrelation-Consistent standard errors, after Newey and West (1987)
HCC	Heteroscedasticity Consistent Covariance estimation as per Bollerslev and Wooldridge (1992); used with QML estimation
HGG*	Henderson Global Care Growth A Income (* denotes an ethical fund)
IIE*	Insight Investment Evergreen (* denotes an ethical fund)
IIG	Insight Investment Global Eq (peer to IIE*)
IIM	Insight Investment Monthly Income (peer to FPS*, AAM*, AEG*, SET*)
IPR	INV-PERP Rupert Childrens (peer to AEG*)
IPU	Invesco Perpetual UK Equity (peer to ISG*)
ISG*	ISIS Stewardship Growth (* denotes an ethical fund)
IUG	ISIS UK Growth & Income fund (peer to FCE*)
JPE	JPMF Premier Equity Growth (peer to ISG*)
JUP*	Jupiter Ecology Fund (* denotes and ethical fund)
LGW	Legal & General Worldwide (peer to HGG*)
MCB	Martin Currie IF Bal P'folio (peer to CFE*, IIE*)
MCI	Martin Currie IF Income fund (peer to FCE*)
MCU	Martin Currie IF UK Growth (peer to AAM*, SET*)
MGG	M&G Global Leaders (peer to FRA*)
MIE	MGM International Eq Growth (peer to CFE*)

MLU	Merrill Lynch UK Smaller Cos (peer to SWE*)
MSS	MGM Special Situations Growth (peer to AAM*, SET*)
MSU	Marks & Spencer UK Select (peer to ENV*)
NBA	Newton Balanced (peer to FRA*)
NIG	Newton International Growth (peer to JUP*)
NII	Norwich Int'l Index Tracking (peer to ENV*, HGG*))
NSM	New Star Maximum Income (peer to FPS*)
NSU	New Star UK Capital Growth (peer to FPS*)
NUE	Norwich UK Equity Income (peer to ENV*)
NUS	Norwich UK Smaller Cos (peer to SWE*)
OIEC	open ended investment company (similar to a unit trust)
OLS	ordinary least squares; the commonest method of estimating a regression line
PARCH	Power GARCH
QGG	Quilter Global Growth (peer to HGG*)
QML	quasi-maximum likelihood estimation; the application of maximum likelihood estimation in circumstances where the normality assumption is not known to be satisfied using a 'robust' estimator
RIG	Rathbone Income & Growth (peer to AAM*, SET*)
RSS	sum of squared residuals from a regression ('residual sum of squares')
RUB	Rensburg UK Blue Chip Growth (peer to AAM*, AEG*, SET*)
SAI	Scottish Amicable Eq Income (peer to SWE*, FPS*, AEG*, SET*)

SAS	Scottish Amicable Equity Strategy (peer to AAM*, SET*)
SBC	Schwarz Bayesian (Information) Criterion
Sedol	Stock Exchange Daily Official List number
SET*	Sovereign Ethical (* denotes an ethical fund)
SGE	Schroder Institutional Global Equity Acc (peer to IIE*)
SIG	Sovereign International Gth (peer to JUP*)
SIN	Sovereign Income (peer to AAM*, AEG*, SET*)
SIO	Schroder Institutional O'seas Eq (peer to ENV*)
SJP	St James's Place UK Income (peer to ENV*)
SMI	Smith & Williamson Income (peer to AAM*, AEG*, SET*)
SMU	Scottish Mutual UK Equity (peer to ISG*)
SMR	Standard Managed Ret (peer to JUP*)
SOU	Sovereign UK Growth (peer to AEG*, SET*)
SPO	Schroder Portfolio (peer to HGG*)
SWE*	Scottish Widows Ethical (* denotes an ethical fund)
SWG	Smith & Williamson Growth (peer to AEG*, SET*)
SWI	Scottish Widows UK Eq Income (peer to ENV*)
SWS	Scottish Widows UK Sp Sits (peer to AAM*, AEG*, SET*)
SWU	Scottish Widows UK Eq Growth (peer to ENV*)
SOU	Sovereign UK Growth (peer to SWE*)

SRI	socially responsible investment, treated here as broadly synonymous with ethical investment (although some authors do argue for differences in meaning)
SUG	Solus UK Growth Fund (peer to FCE*)
SWG	Smith & Williamson Growth (peer to SWE*)
SWT	Smith & Williamson Thoroughbred (peer to IIE*)
TARCH	Threshold GARCH
THO	Thornhill American (peer to IIE*)
WAY	WAY Global Red Portfolio (peer to IIE*)

The Performance of UK Ethical Investment Funds

1. Introduction

This introductory chapter presents the aim and the objectives of the present research.

Also, to assist readers, section 1.3 on p.2 provides a brief explanation of the rationale behind the thesis structure shown in the table of contents on p.356.

1.1 Aim

- To investigate the financial performance of a selection of UK ethical investment funds in comparison to relevant market benchmarks and to similar non-ethical funds.

In pursuit of this aim four objectives have been identified.

1.2 Objectives

1.2.1 Objective One

- to review current knowledge and identify research opportunities

1.2.2 Objective Two

- to investigate whether the unusual switch of the Family Charities Ethical fund from conventional to ethical investment objectives affected its financial performance

1.2.3 Objective three

- to investigate the financial performance of 12 funds that have been ethical since launch

1.2.4 Objective Four

- to examine the sensitivity of ethical fund performance measurement to researcher-chosen parameters (choice of equilibrium model, time period analysed, non-ethical funds selected for comparison, how – if at all – variance is modelled)

1.3 Structure Of The Thesis

The thesis follows the generally-accepted format and structure, but in a relatively large document a brief overview is perhaps useful.

Chapter 2 Literature Review on p.4 provides the usual literature review. Following a brief introduction to ethical investment (section 2.2 on p.4) the present research is located in relation to current knowledge and the academic literature, first broadly (section 2.3 on p.7) and then in a more detailed way (section 2.4 on p.10). Since the present research is closely related to a single recent publication – Kreander et al. (2005) – advantage is taken of this fact to provide structure and brevity. A number of opportunities to extend the methods of analysis are identified, in line with objective one above. The chapter begins with a 'chapter overview' and ends with 'chapter conclusions'.

The usual discussion of data to be analysed is split into two parts in chapters 3 and 4.

Chapter 3 Data I: Family Charities Ethical (FCE*) on p.26 introduces ethical fund Family Charities Ethical in some detail, as this is an unusual fund that was initially 'non-ethical' or 'conventional' and later adopted ethical investment objectives. 'Conventional' or 'non-ethical' funds similar to Family Charities Ethical are also identified. Family Charities Ethical provides an unusual opportunity to investigate whether its change in investment objectives had an effect on financial performance, as per objective two above.

(Note: in what follows all funds are given a three-letter abbreviated label to which is added an asterisk if the fund is ethical; the full fund name is given in the list of Acronyms and Abbreviations on p.xvii.)

Chapter 6 Analysis I: Family Charities Ethical (FCE*) on p.89 presents the results from analysis of the Family Charities Ethical fund. An abrupt change in financial performance is found, the temporary nature of which might be taken as evidence of ethical fund manager learning.

Chapter 4 Data II: Twelve Ethical Funds on p.34 – a second 'data chapter' – introduces a further 12 more typical ethical funds that have been 'ethical' since launch and also assigns to these similar 'conventional' or 'non-ethical' funds.

Chapter 7 Analysis II: Twelve Ethical Funds on p.108 – a second 'analysis chapter' – presents the results from analysis of the 12 ethical funds firstly individually, then in groups, and then using cross-sectional regression similarly to previous researchers. A large quantity of information is necessarily presented in this chapter, but a useful (if somewhat over-simplified) concise summary is provided in section 7.14 on p.167.

Chapter 5 Methods of Analysis on p.60 describes in detail the methods used in achieving the above. A major feature is the use of generalised auto-regressive conditional variance - GARCH – models to explicitly model the variance of fund returns in a way not previously done, so far as is known, with ethical investment funds. It is argued that doing so provides more accurate estimates of mean fund performance in addition to generating information that is of interest in its own right.

Implementation of this analysis was done by means of batch programs run on Eviews 5.1 software. An example of such a program is provided in Appendix D: Example Eviews 5.1 Batch Program on p.329.

Earlier research on the Family Charities Ethical fund was published as Mill (2006) which is provided here as Appendix E on p.346.

Chapter 8 on p.185 provides the usual conclusions in relation to the objectives above.

Chapter 9 on p.193 provides recommendation for further research.

2. Literature Review

2.1 Chapter Overview

A brief introduction to ethical investment and socially responsible investment is provided in section 2.2.

Section 2.3 Broad Research Context on p.7 briefly describes the different strands of published academic ethical investment performance research, and how the present research sits in relation to these.

Section 2.4 Detailed Research Context on p.10 considers the more closely relevant publications in more detail. This is done in three parts, aided by the fact that the present research is very similar in intent and method to Kreander et al. (2005).

Firstly, in part 2.4.1 on p.10, those publications cited by Kreander et al. (2005) as having informed their research are discussed and the relationship to the present research is described.

Secondly, Kreander et al. (2005) itself, of course, raises a number of points of interest for the present research beyond the preceding literature, and these are discussed in section 2.4.2 on p.16.

Thirdly, a modest number of publications of interest are not mentioned in Kreander et al. (2005), and these are discussed in section 2.4.3 on p.18.

Section 2.5 on p.20 briefly reviews theories in the literature relating to why the performance of ethical funds might be expected to be the same as conventional funds, or to be either inferior or superior.

Section 2.6 on p.23 concludes the chapter.

2.2 Introduction to Ethical Investment

Ethical investment is a growing international phenomenon. Within Europe, in addition to Sweden (where the first ethical retail fund was established in 1965) and the UK (the largest European ethical investment market) ethical funds operate in Belgium, France, Germany, Norway, Switzerland, the Netherlands, Austria, Finland, France, Spain and

Italy (Kreander, 2001). At the end of 2005 there were 75 ethical funds in the UK with around half a million accounts totalling £6.1 billion (Eiris, 2006) and by January 2007 this number had increased to 90 (Eiris, 2007).

Total European ethical investment assets in 2002 were estimated at €19.8 billion with well over 200 ethical investment funds. By 2006 the broad European ethical investment market was estimated to total €1 trillion representing up to 10% or 15% of European managed funds (Eurosif, 2006). US 'socially responsible investment' assets were estimated to total $2.29 trillion in 2005, of which $179 billion was in 'socially screened' mutual funds similar to those investigated in what follows (Social Investment Forum, 2006). Australian ethical investment has been estimated at from A$2 billion to A$10.5 billion; Canada has around 50 ethical investment funds; Japan is rapidly developing a distinctive form of ethical investment; these trends continue to grow (Sparkes, 2002).

Most of the above ethical investment activity is relatively recent, however, with longer-established ethical investment funds commonest in the US and UK. Broadly similar accounts of the "astounding escalation" in ethical investment can be found for example in Waring and Lewer (2004) and Schueth (2003).

Much of the information in the initial paragraph of this section was taken from sources referring to "socially responsible investment"; other sources referred to "ethical investment". "Ethical investment" is similar in meaning to "socially responsible investment" (increasingly commonly abbreviated to SRI) although they are arguably not exact synonyms. While meaningful distinctions are at times made between these two terms (see for example Sparkes and Cowton, 2004; Sparkes 2002) both refer to:

> *...the exercise of ethical and social criteria in the selection and management of investment portfolios, generally consisting of company shares (stocks). (Cowton, 1994)*

Cowton continues:

> *This contrasts with the standard depictions of investment decisions, which concentrate solely on financial return... Ethical investors care not only about the size of their prospective financial return and the risk attached to it, but also its source – the nature of the company's goods and services, the location of its business or the manner in which it conducts its affairs.*

The question of whether such additional considerations impact on financial return follows naturally from this definition.

In what follows the term "ethical investment" will generally be used in preference to "socially responsible investment". It frequently arises that reference must be made to the 'other' similar, more common, investments that are not concerned with ethical criteria, but solely with financial return. In what follows these are referred to either as 'conventional' or as 'non-ethical' investments. This is simply a matter of convenient terminology, and carries no implication that 'non-ethical' investments are in some way unethical or immoral. Where non-ethical funds have been chosen to be similar to a particular ethical fund they are referred to in what follows as 'peers'.

Most individual ethical investors utilize mutual funds in North America, and unit trusts or Open-Ended Investment Companies (OEICs) in Europe. The latter are the focus of the present research. An indication of how conventional and ethical funds differ is given by the example of fund FCE* which changed from conventional to ethical investment objectives as described in section 3.2 on p.26. The investment objectives of its conventional peers are described in section 3.3 on p.29. The ethical investment objectives of a further dozen ethical funds are described in section 4.4 on p.38.

Some institutions with significant assets manage their own ethical investment portfolios, for example the Methodist Church and the Society of Friends (Quakers) in the UK and The Norwegian Government Petroleum Fund which adopted ethical investment principles in November 2004 making it possibly the largest ethical investment fund anywhere (Norwegian Ministry of Finance, 2005).

Recent expansion of ethical investment activity in the UK, Germany and Australia has arisen due to the adoption of ethical investment by large institutional investors such as pension funds and insurance companies, encouraged by regulatory change. In the UK, amendments to section 35(3)(f) of the 1995 Pensions Act came into force in July 2001, requiring all occupational pension funds to state "the extent (if at all) to which social, environmental or ethical considerations are taken into account in the selection, retention and realisation of investments..." (HMSO, 1999). The UK pension fund market (£800 billion in 2000) is vast in comparison with the retail ethical fund market (£3.3 billion at that time).

Ethical investment objectives have also been adopted by some pension funds, for example the BT Pension Scheme (£29 billion) and the Universities Superannuation Scheme (£22 billion). A survey of the 500 largest UK pension funds and 97 local authority pension funds found that 59% of respondents, representing 78% of assets, were intending to adopt ethical investment criteria (Green, 2001). Another survey of pension fund trustees found that 69% had a statement of investment principles featuring ethical or social responsibility issues, and a majority felt that social, environmental and employment practices, and good corporate governance generally, impacted on market value, particularly in the longer term (Gribben and Olsen, 2003; see also Gribben and Faruk, 2004).

The present research is firmly focussed on the financial performance of ethical investments in the form of unit trusts/OEICs, and this focus has informed the literature review that follows from section 2.3 onwards. The general introduction in this section has been kept brief, but good sources of more general information on ethical investment are Hancock (2005) and Sparkes (2002). Also good but now a little out of date are Hancock (1999), Lang (1996) and Sparkes (1995).

A special issue of the Journal of Business Ethics in June 2004 provides a good starting point into the general academic literature, with Cox et al. (2004), Haigh and Hazelton (2004), Hockerts and Moir (2004), McLachlan and Gardner (2004), Michelson et al. (2004), Sparkes and Cowton (2004) and Waring and Lewer (2004). These authors also provide useful discussion of and reference to other important work not directly relevant to what follows below, for example Lewis and Mackenzie (2000a, 2000b) on the psychology and attitudes of ethical investors.

2.3 Broad Research Context

The empirical question of the financial performance of ethical investments has been approached in more than one way, not always examining unit trusts as is done here.

One strand of ethical investment performance research has examined published ethical (or socially responsible) market indices such as the US Domini 400 Social Index (e.g. much of Camejo, 2002; Sauer, 1997) or indices specially-produced for the purpose (Havemann and Webster, 1999).

In a second strand of the literature, a number of (mainly US) studies examine the performance of specially-constructed ethical and non-ethical portfolios of company shares (Bibartolomeo and Kurtz, 1996; Butz and Plattner, 2000; Diltz, 1995; Guerard, 1997; Stone et al., 2001). This is quite distinct from examination of how actual existent ethical funds into which individuals may invest ('retail' funds) have fared. The use of specially-constructed portfolios makes it possible to control for performance effects due not to 'ethicalness' as such but to 'coincidental' concentration in investment sectors (such as smaller companies or IT and communications) that are doing well or badly over a given period of time. The aim is to isolate a distinct ethical investment effect if one exists.

A third strand of the literature investigates the performance of actual retail ethical investment funds as opposed to published indices or portfolios constructed by researchers. Since individual 'retail' investors in a mutual fund or unit trust/OEIC experience the overall net effect of the ethical investment approach, along with any accompanying small company effects or investment sector effects, this approach seems better able to inform current or would-be ethical investors, and is adopted here.

The financial performance of actual ethical investment funds has been most studied in the UK and other European countries. The first such study appears to be Luther et al. (1992), followed by Luther and Matatko (1994). Mallin et al. (1995) introduce the 'matched pair' approach referred to below, while Gregory et al. (1997) use a cross-sectional regression technique in addition to pairwise comparisons of 'ethical' and 'non-ethical' funds. Kreander et al. (2002) considerably develop Mallin et al.'s 'matched pair' approach in terms of model used and statistical approach and expand consideration to seven European countries. This is followed by Kreander et al. (2005), discussed below. Bauer et al. (2002) analyse 103 ethical funds from Germany, the UK and the USA. Hamilton et al. (1993), Geczy et al. (2003) and Statman (2000) consider the performance of actual US ethical funds, while Bauer et al. (2003a) do likewise for Canadian funds and Cummings (2000) and Bauer et al. (2003b) for Australian funds.

The broad picture to emerge from the above studies (subject to various caveats regarding benchmarks, risk factors, choice of funds for analysis and comparison, etc.), is that there is little evidence of ethical funds over-or under-performing relative to the market (although some studies find that both ethical and non-ethical funds under-perform relative to the market), and also little evidence of a difference between the ethical and non-ethical groups. Ethical funds appear on the whole to follow the market similarly to their non-ethical counterparts, each group generally failing to 'beat the market' in a statistically significant way but also not generally underperforming relative to the market.

The above studies of actual ethical funds all have two broad features in common.

Firstly, throughout the time period under consideration, a given fund or portfolio is always either ethical or non-ethical and in this sense the comparisons made are cross-sectional. Almost all funds are initially launched either with or without ethical investment objectives (the vast majority without), and this very rarely changes.

Secondly, although the variability of returns is generally taken into account in as much as 'risk-adjusted' performance measures are used, attention is firmly focussed on the mean level of returns over time.

The present research differs with regard to both of these features.

Firstly, Family Charities Ethical (FCE*), a UK unit trust, was initially launched with conventional investment objectives and subsequently 'became ethical'. This provides an unusual opportunity to make a time-series comparison of conventional pre-ethical and post-ethical performance. FCE* is introduced in chapter 3 on p.26 and results from its analysis are presented in chapter 6 on p.89.

Secondly, while the mean level of returns is investigated below in a similar manner to previous studies, considerable attention is also given in the present research to explicit modelling of the variability of returns. It is argued that this explicit variance modelling approach provides more accurate estimates of mean performance than do estimation methods that seek simply to be 'robust'. Also the variability of returns is useful information in its own right, and merits investigation rather than being seen as an obstacle to obtaining reliable estimates of mean performance. The variance modelling approach here (using generalised auto-regressive conditional heteroscedasticity – GARCH – models) is introduced in section 5.3 on p.67 and elaborated upon in section 5.4 on p. 73. This approach is applied to ethical fund FCE* in chapter 6 on p.89, and also to a dozen other ethical funds in chapter 7 on p.108.

2.4 Detailed Research Context

The present research is very close in intent and method to the work of Kreander et al. (2005), and also extends this in some ways. Kreander et al. (2005) studied the performance of 30 ethical funds from four European countries matched with similar non-ethical funds or 'peers'.

Kreander et al. (2005) itself builds on previously published work by Black, Fraser and Power (1992), Brown and Goetzmann (1995), Carhart (1997), Chen et al. (1992), Choi and Murthi (2001), Daniel et al. (1997), Draper (1986), Fama and French (1998), Ferson and Schadt (1996), Fletcher (1995), Gregory et al. (1997), Grinblatt and Titman (1989, 1994), Henriksson (1984), Henriksson and Merton (1981), Kreander et al. (2002), Liljeblom and Loflund (2000), Luther and Matatko (1994), Luther et al. (1992), Mallin et al. (1995), Nesbitt (1995) and Statman (2000).

The remainder of this section outlines, in part 2.4.1, how the Kreander et al. (2005) research builds on the work of these authors and also how this relates to the present research. This is followed in part 2.4.2 on p.16 by consideration of some further issues in Kreander et al. (2005) not arising from previous literature. Part 2.4.3 on p.18 completes this review of the detailed research context by considering relevant publications not cited in Kreander et al. (2005).

2.4.1 Papers Cited in Kreander et al. (2005)

Academic enquiry into the financial performance of UK ethical funds was begun by Luther et al. (1992) who found "weak evidence of some overperformance, on a risk-adjusted basis, by 'ethical' unit trusts" (their p.68). In addition to other types of analysis Luther et al. used monthly data in a market model regression (their p.62) to estimate fund performance measures using two different benchmark indexes, one domestic (FT All Share) and the other international (MSCIP World index). Much of their discussion concerns which of these benchmarks is most appropriate. There is no direct comparison of ethical funds with non-ethical funds. It is notable that Luther et al. use the market model of equation (4) on p.66 below whereas for similar purposes all subsequent research has used the alternative capital asset pricing model (CAPM) of equation (1) on page 62 (or variations on this). This difference seems not to be remarked upon in subsequent publications. It is argued in section 5.2.3 on p.64 below that the market model is preferable.

Luther and Matatko (1994) – two of the three authors in Luther et al. (1992) – investigate 9 ethical funds, addressing similar concerns regarding the choice of appropriate benchmark and proposing the use of a two index model with a small company index (the Hoare Govett smaller companies index used in the present research) in addition to a broad market index (in this case the FT All-Share Actuaries index rather than the FT All Share). Luther and Matatko (1994) utilise the CAPM with the return on 30 day Treasury bills for the risk free rate, using monthly data. This change of method from Luther et al. (1992) is not explained or, indeed, mentioned. Luther and Matatko (1994) note that the collinearity between the two market indices makes estimation of the slope coefficients unreliable, but propose that "it is necessary to include both indices" (p.87) as adjusted-R^2 is higher for the two index model – which in itself is perhaps not entirely sufficient support for the two index model. The implication seems to be that the two index model may provide more reliable intercept estimates (used to assess performance) although they do not quite say this; however they find that "no matter what benchmark is used... mean abnormal returns are almost always insignificantly different from zero" (their p.87).

Mallin et al. (1995) have greatly influenced subsequent research, including the present research, by comparing monthly observations on 29 UK ethical funds not only with a market index but also with similar non-ethical funds matched on the basis of fund age and size to produce a set of 'matched pairs' in which each ethical fund is compared with a single non-ethical fund. The present research argues that the 'matched pair' approach is unnecessarily restrictive and employs a development of the technique (see sections 3.3 on p.29 and 4.5 on p.45). Mallin et al. also use the CAPM but now with the return on 3-month Treasury bills as the risk-free rate of return, and also express concern about the choice of market index used for all funds, opting for the FTSE Actuaries index used by Luther and Matatko (1994). Mallin et al. conclude that they find evidence of "weakly superior performance of ethical funds" (their p.495) relative to the matched non-ethical funds but also find that "both ethical and non-ethical funds tend to underperform the market" (p.494).

Gregory et al. (1997) – (the authors include both Matatko and Luther of the previous studies) – build on the work of Luther and Matatko (1994) and Mallin et al. (1995). They note that some of Mallin et al.'s age-and-size-'matched pairs' may not have been closely similar in terms of investment focus, and add to the age and size matching criteria two more: fund type (general, growth or income) and geographical focus of investment. Such broadening of matching criteria is adopted in the present research (see section 4.5.1 on p.45) which considers investment sector and nominated benchmark index in addition to age and size. Gregory et al. (1997) again utilise the CAPM using monthly data now with the FT All Share index as broad market index together with the Hoare Govett smaller companies index (in a different way to Luther and Matatko (1994), so as to resolve the collinearity problem) to produce a 'size-adjusted' performance measure. Gregory et al. (1997) find no significant over- or under-performance of ethical funds relative to the market benchmark(s) or to the matched non-ethical funds. They also stress the importance of adjusting for a fund's tendency to invest in smaller companies, and find that the age of a fund (but not the size of a fund) may affect performance (with newer funds somewhat under-performing). A cross-sectional regression of individual fund results appears to have been first used by Gregory et al. (1997) in the context of ethical investment performance.

Gregory et al. (1997) use monthly price and dividend data and follow common good practice (e.g. Mills, 1990) by taking the logarithm of these in order to help reduce the effect of likely departures in the data from the normal probability distribution. This procedure is also adopted by Kreander et al. (2005). The present research differs in this respect as it makes use not of raw price and dividend data from which returns are calculated, but of a total monthly return index supplied from Reuters Hindsight database. The question of deviations from normality is dealt with in a different way, testing the residuals of each model for normality, and adopting the 'robust' estimation method of Bollerslev and Wooldridge (1992) in those cases where the hypothesis of normality is rejected, as described in section 5.6.2 on p.83. It frequently happens that the hypothesis of normality is not, in fact, rejected.

The present research does not utilise the size-adjusted approach of either Luther and Matatko (1994) or of Gregory et al. (1997) (the latter is also used by Kreander et al. (2005)), but is mindful of the concerns in the literature that motivate this approach, regarding the tendency of ethical funds to invest in smaller companies and regarding the correct choice of benchmark.

A key point is that all previous researchers have applied the same benchmark (or combined-benchmark-model) to every fund analysed. In the present research the available data includes the benchmark index nominated by each individual fund – see section 4.5.2 on p.46. It is argued that there is some justice, then, in comparing each individual fund to the benchmark index that the fund managers have declared to be relevant. In some instances e.g. ethical fund ISG* in Table 4-3 on p.46, ethical fund SWE* in Table 4-5 on p.47 and its matched peer funds MLU, BGI and NUS, the nominated benchmark index is the Hoare Govett smaller companies index used by Luther and Matatko (1994) and by Gregory et al. (1997). (Note: recall that here all funds are given a three-letter abbreviated label to which is added an asterisk if the fund is ethical; the full fund name is given in the list of Acronyms and Abbreviations on p.xviii.)

For the purposes of broad comparability, the present research also repeats the analysis using the FTSE All Share index (in some instances a broad international index may have been more appropriate: see recommendation 5 in chapter 9 on p.193).

Statman (2000) undertook similar research on US ethical mutual funds using both the 'conventional' Standard & Poor 500 index and the 'ethical' Domini Social Index. These were not combined in a single model as proposed by Luther and Matatko (1994) and Gregory et al. (1997), rather the analysis was repeated with each index. In a precedent to the broadening of Mallin et al.'s (1995) 'matched pair' approach in the present research, Statman assigns two non-ethical funds to each ethical fund for comparison, based on fund size. The present research assigns a varying number of non-ethical funds (from 3 to 19) to each ethical fund using consistent criteria.

Statman reaches conclusions similar to those of Mallin et al. (1995): ethical funds do slightly better than the similar non-ethical funds, but both groups considerably underperform relative to both the broad S&P 500 index and the Domini Social Index. However, Statman illustrates a tendency also evident in preceding publications (e.g. Mallin et al.'s "weakly superior performance") when he says that the ethical funds:

> *...performed better than conventional funds of equal asset size, although the difference was not statistically significant (p.38).*

This seems a little unreasonable. If no statistically significant difference is found, then this implies that any observed difference is due either to random 'noise', or to misspecification of the model (for example, perhaps an important explanatory variable is omitted). In such circumstances, it seems much more reasonable to report the result of the statistical test – that no difference has been found (subject to the relevant caveats) – rather than to report, as Statman does, that a difference has been found that somehow fails to be statistically significant.

Such wishful thinking in the interpretation of results ('there is a difference... it's just not statistically significant...') is a problem facing all researchers. An attempt is made in the present research to avoid such wishful thinking, by focussing on results where differences are statistically significantly different, and by regarding non-statistically-significant differences as effectively zero. This is relaxed a little in circumstances where, due to small sample size, it is known that a test has little power (i.e. small probability of correctly rejecting a false null hypothesis).

This reasoning has also informed a preference in the present research towards the use of 'Jensen's alpha' α_p, described in section 5.2.2 on p.61, as a performance measure. The analysis delivers for each fund an individual 'alpha' α_p estimate complete with standard error and other information for testing the null hypothesis of equality to zero. By their nature the Sharpe and Treynor performance measures also used by previous researchers do not provide quite the same level of information. A case might be made for an exhaustive approach in which every measure was calculated and reported; this is not done here, although it is noted as a recommendation for future research (recommendation 2 in chapter 9 on p.193).

Survivorship bias is a potential problem in research of this type. Poorly performing funds tend to go into liquidation so that a sample of funds which persist over time will tend to overestimate the performance of funds in general. Grinblatt and Titman (1989) and Brown and Goetzmann (1995) provide some reassurance that this effect is likely to be small. More importantly, there is no reason to suppose that survivorship bias will not affect ethical and non-ethical funds similarly, so the matching procedure introduced by Mallin et al. (1995) provides an antidote to this potential problem.

Possible market timing ability by fund managers, meaning an ability to vary the covariance between fund returns and the market as a whole so that this covariance is higher when the market is rising, lower when the market is falling, is potentially an important consideration. In addition to being of interest in its own right, market timing can lead to inaccurate estimates of 'alpha' α_p (a performance measure, as described in section 5.2.2 on p.61) if not adequately accounted for. If market timing is present i.e. if this covariance is not constant and 'alpha' α_p is estimated in a manner that assumes that it is constant, the resulting 'alpha' α_p estimate is unreliable, as demonstrated by Black, Fraser and Power (1992); see also Draper (1986).

Kreander et al. (2005) are the first to allow for market timing in ethical fund performance measurement, introducing a measure of market timing proposed by Henriksson and Merton (1981). Kreander et al. find no funds with statistically significant positive timing ability, but a number with negative timing ability (which is equally a possible source of misspecification error in the estimation of 'alpha' α_p). This agrees with the results of Chen et al (1992), Daniel et al. (1997), Ferson and Schadt (1996), Fletcher (1995), Henriksson (1984), Liljeblom and Loflund (2000) and Nesbitt (1995). The present research uses the Henriksson and Merton (1981) timing measure used by Kreander et al. – see equation (2) on p.63 - and also an alternative timing specification not previously used in ethical investment research, proposed by Treynor and Mazuy (1966) – see equation (3) on p.64. The specification which best fits the particular data is chosen.

Newey and West (1987) provide a method for calculating 'robust' standard errors and p-values for the usual hypothesis tests on regression coefficients. This method can overcome estimation problems that occur with the usual ordinary least squares estimation method if the assumption of constant variance of residuals is violated, as it is expected to be in time series financial market data, (i.e. if there is heteroscedasticity). The Newey and West method is used by Kreander et al. (2005) as noted in a footnote to their table 4a, p.1483, but the choice of this method is not discussed in Kreander et al.'s text. In the present research the heteroscedasticity problem is discussed in some detail in section 5.3 on p.67 where an alternative to the Newey and West approach is described. Explicit variance modelling using GARCH models instead of the Newey and West 'robust' approach is one of the main novel features of the present research.

Another assumption on which ordinary least squares estimation rests is that there is a lack of serial correlation in the residuals. Violation of this assumption has rather similar consequences to violation of the constant variance assumption in the previous paragraph (Gujarati, 1995, p.400) (standard errors and p-values, but not mean coefficient estimates, become unreliable). The cross sectional regression used by Kreander et al. (2005) and predecessors (and also in the present research, see section 7.16 on p.176) to compare estimated performance measures across funds is likely to suffer from this problem. Noting this potential problem, Kreander et al. use a corrective procedure proposed by Grinblatt and Titman (1994). However, Kreander et al. do not seem to report on whether a test was first conducted to establish the actual presence or absence of this potential problem in their results.

In the present research both the Breusch-Godfrey serial correlation LM test (Godfrey 1988) and Ljung-Box Q-statistics (Ljung and Box 1978) from a correlogram of residuals were used to test the null hypothesis of no serial correlation in all cross sectional regressions (see for example Table 7-30 on p.179, Table 7-32on p.181, Table 7-33 on p.181 and Table 7-34 on p.182). Since this null hypothesis failed to be rejected, the ordinary least squares estimates were considered to be acceptable and the Grinblatt and Titman procedure was not used.

2.4.2 Further Considerations From Kreander et al. (2005)

The previous section describes how the present research sits in context with previous research reported in and built upon by Kreander et al. (2005). Of course, Kreander et al. (2005) itself raises some points of interest beyond the preceding literature. This section considers how these relate to the present research.

Kreander et al. (2005) is notable in its use of data of weekly frequency, whereas previous researchers used monthly data. The increase in number of available observations that weekly data provides would have been very welcome in the present research. Indeed, the GARCH models that form a significant feature here are often used with data of still higher frequency: "...GARCH models... are commonly used for modelling the volatility of daily returns" (Alexander 2001). Alexander (2001) then proceeds to discuss their use with intra-day data.

Use of data with frequency higher than monthly would be desirable and is undoubtedly a relative weakness of the present research, which uses monthly data. For example, the greater number of observations that this affords would allow for GARCH model selection by likelihood in post-sample predictive tests as recommended by Alexander (2001, p.97). In the present research post-sample forecasting was considered unreliable given the limited number of observations available (around 150), and other means of model selection are employed, as described in section 5.6 on p.82.

The initial use of monthly data in the present research is in line with pre-Kreander et al. (2005) research. In the present research it did not prove possible to obtain further higher-frequency data at a later date due to an unexpected general difficulty that was experienced in obtaining what is, in principle, publicly-available data. Initial use was made of the DataStream financial database to which De Montfort university subscribes. However, this was found to be unreliable with many omissions in the data. It was confirmed by university librarians that others have experienced similar problems with DataStream and the subscription has since been discontinued. Access was gained to the very useful Reuters Hindsight database used by a firm of ethical financial advisors, but this access was only temporary and did not allow for revisiting to gain further data. For similar reasons the present research is also somewhat restricted in the cross sectional explanatory variables considered. Here fund size and age are used, but Kreander et al. (2005) also discuss other interesting possibilities that are not explored here. Similarly, it was not possible to revisit the analysis with the Carhart (1997) multi-factor model used by Bauer et al (2002, 2003a, 2003b) discussed in the next section, although this is noted as a recommendation for further research (recommendation 8 in chapter 9 on p.193).

In the specification of the cross sectional regression equation, Kreander et al. (p.1478, their equation 7) introduce a dummy variable to estimate any difference between ethical and non-ethical funds. This takes the form of an intercept dummy variable, which, as the name suggests, allows for estimation of two different intercept coefficients, one for ethical funds and the other for non-ethical funds. This specification imposes the condition that the relationship between fund performance and each explanatory variable: size, age, etc., is identical for ethical and non-ethical funds, which seems unnecessarily restrictive.

The present research utilises both intercept dummy variables and slope dummy variables, as illustrated in equation (5) in section 5.2.4 on p.66 (this example deals with a time series regression, but the same principle is applied to the cross sectional regressions reported in Table 7-30 on p.179, Table 7-32on p.181, Table 7-33 on p.181 and Table 7-34 on p.182). This refinement turns out not to produce especially interesting results, as the slope dummy coefficients all turn out to be statistically insignificantly different from zero. However it is preferable that this has been demonstrated, rather than assumed, to be so.

Kreander et al. (2005) provide an interesting discussion suggesting that international ethical funds may perform better than those with a domestic focus. While this is a very reasonable hypothesis, the results of the present research do not support it (see conclusion 3.17 in section 8.3on p.187).

2.4.3 Other publications

There are a small number of research publications not discussed in Kreander et al. (2005) that are of relevance to the present research.

Hamilton et al. (1993) use the CAPM with monthly data to examine the performance of 32 US ethical mutual funds. Interestingly, they appear to be the first to have compared ethical funds not only with published market indices but also with comparable non-ethical funds, as their research pre-dates Mallin et al. (1995) who are often credited with this. Hamilton et al. make this comparison not by means of Mallin et al.'s 'matched pairs' but by constructing a benchmark portfolio of non-ethical funds, an approach that appears not to have been used with UK data. Hamilton et al. (1993) find no statistically significant difference in the performance of ethical funds relative to the market index or to the non-ethical fund benchmark.

Cummings (2000) is an interesting study of seven Australian ethical investment funds using the CAPM with monthly data. A novel feature is the use of a third industrial sector index in addition to the two indices recommended by Luther and Matatko (1994) and Gregory et al. (1997) (a broad market index and a smaller companies index). No comparison is made with non-ethical funds. Cummings finds an "absence of significant difference in performance by ethical trusts against the benchmarks" (p.87). Cummings also remarks on the diversity amongst the seven ethical funds, speculating that "analysis of the investment policies of each of the ethical trusts may provide an insight into the reasons behind the differing performance levels" (p.87). Diversity of investment objectives is very evident in the funds considered in the present research (see section 4.4 on p.38) and although detailed analysis of investment polices was not carried out in the present research, two funds – FRA* and JUP* – stand out as having a policy different from the other funds, and is also found to have distinct financial performance (in terms of variability, not mean returns). So far as is known, this admittedly limited instance is the only published example linking differences in investment objectives with differences in fund performance (see conclusions 3.2 and 3.4 in section 8.3 on p.187).

Bauer et al. (2002) is the first in a sequence of three extremely interesting papers on ethical fund performance whose implications for future research appear to be considerable. The authors examine 103 German, UK and US ethical funds using the CAPM with monthly data and also "solve the benchmark problem" using the Carhart (1997) four-factor model and also an extension of this with conditional (i.e. time-varying) beta. Using the CAPM Bauer et al. find that the performance of ethical funds is less well explained by ethical indices such as the Domini Social Index (US), the Dow Jones Sustainability Global Index (used for German funds) and an Eiris index (UK) than by broad market indices, on which they remark: "this raises the question whether ethical funds are really following distinct ethical investment styles" (p.8). Using simpler models Bauer et al. find no statistically significant differences between ethical and non-ethical funds. With the conditional time-varying-beta four factor model there is a statistically significant negative difference between US ethical and non-ethical funds and a statistically significant positive difference between UK ethical and non-ethical funds (i.e. UK ethical funds perform better than their peers; US ethical funds worse).

Bauer et al. (2002) also look at changes in ethical fund performance over time, finding evidence of a learning effect such that "after a period of strong under-performance, older ethical funds finally are catching up, while younger funds continue to under-perform both the index and conventional peers" (p.14). In a different way, relating to variability about the benchmark index, the present research also finds evidence suggestive of a fund manager learning effect (see recommendation 11 in chapter 9 on p.193).

Bauer et al. (2003a) is similar, but examines 8 ethical and 267 conventional Canadian funds, concluding that "there is no significant performance difference between ethical mutual funds and their conventional peers" (p.17).

Bauer et al. (2003b) is again similar, examining 25 ethical funds and 281 conventional funds, concluding that "Australian ethical funds do not under-perform relative to conventional funds" (p.18). They also find a learning effect such that "after significant under-performance in the beginning of the 1990s, they [ethical funds] match conventional fund performance more closely during the 1996-2003 period" (p.18).

Finally, there is Mill (2006), reporting on earlier work similar to chapters 3 and 6 on pages 26 and 89 of the present research. Mill (2006) uses a monthly CAPM similarly to previous researchers but with variance modelled using a GARCH(1,1) specification to examine the Family Charities Ethical fund which switched from conventional to ethical investment objectives in March-96. The results are very similar to the more developed analysis presented in chapter 6 on p.89 below, using a market model with the full range of GARCH specifications. Mill (2006) is provided as Appendix B on p.220.

2.5 Theories Of Ethical Investment Performance

The present research is firmly focussed on the empirical question of whether or not the return to ethical funds differs from that of similar conventional funds. As noted above, there is a small but growing body of evidence suggesting that the performance of ethical funds is broadly similar to conventional funds and can at times be superior. If this is truly the case, an obvious obstacle to the wider adoption of ethical investment practices is removed.

Alongside the empirical literature is a literature reflecting a variety of views regarding whether or not a difference in ethical/conventional fund performance is likely, the expected direction of any such difference, and the factors that might produce it. This section aims to provide a brief overview of this literature.

It is commonly believed that ethical investment must entail financial sacrifice as, for example, in a memorable article entitled 'Why I Invest With Sinners':

> *Capital allocated by bleeding heart instead of invisible hand ends up in places where the owners can feel good about it, not where it can make the most of itself... (Rothchild,1996, p.197)*

The starting point for more rigorous discussion must be the efficient market hypothesis. As noted by Cambell et al. (1997) the modern economic literature on capital market efficiency begins with Samuelson (1965) and owes much to the classic surveys of Fama (1970, 1991). A useful definition is later provided by Malkiel (1992):

> *A capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices. Formally, the market is said to be efficient with respect to some information set... if security prices would be unaffected by revealing that information to all participants. Moreover, efficiency with respect to an information set... implies that it is impossible to make economic profits by trading on the basis of [that information set].*

Three classes of information sets are generally distinguished and thus three levels of market efficiency:

- weak-form efficiency: only the history of prices or returns
- semi-strong-form efficiency: all publicly available information
- strong-form efficiency: all information, including private information held by 'insiders'

Since both conventional and ethical fund managers are generally making use of publicly available information, in a semi-strong efficient market members of neither group would be able to consistently generate investment returns above the equilibrium level. The evidence in support of semi-strong efficiency is "quite strong" (Pilbeam, 1998). Thus ethical funds might be expected to perform very similarly to conventional funds. Note that the efficient market hypothesis implies that both conventional and ethical funds will each equally fail to consistently 'beat the market'.

On the other hand, processing 'all publicly available information' is a large task and therefore not costless. Ethical and conventional funds differ in their view of which subsets of 'all publicly available information' should be used to inform investment decisions, with ethical funds considering a wider range of information. In a semi-strong efficient market, this additional public information utilised by ethical funds cannot affect financial performance, so that the additional information costs incurred would seem to imply a lower net return to ethical investors.

A "more practical version of the Efficient Markets Hypothesis" is proposed by Lo and MacKinlay (1999), as follows.

> *Despite the occasional "excess" profit opportunity, on average and over time, it is not possible to earn such profits consistently without some type of competitive advantage e.g. superior information, superior technology, financial innovation, etc. (Lo and MacKinlay 1999, p.7)*

The question then becomes: is there any reason to suppose that ethical funds might have such a competitive advantage? The factors that might influence the performance of ethical funds appears to have been considered rather little. A notable contribution by Sparkes (1995) posits five 'effects' that may operate, later revisited and discussed in Sparkes (2002).

Diversification effect:
any non-financial restriction on investment selection must reduce diversification, hence risk-adjusted returns

Small companies effect:
socially responsible investors are forced to avoid large conglomerates and concentrate on smaller companies which over time grow faster

Anticipation effect:
exclusion of certain companies on grounds of moral or environmental repugnance anticipates later legal action and financial problems

Information effect:
to do it properly, SRI needs a higher level of knowledge about the companies invested in than ordinary investment managers possess

Positive selection effect:
the positive criteria used by such funds helps them target well-run companies (Sparkes, 2002).

The diversification effect is in practice likely to be small, even effectively zero. It a well established result of portfolio theory that adding further assets to a portfolio reduces portfolio variance (so long as the new asset is not perfectly correlated to any previously held asset, which is unlikely). However, the marginal reduction in variance available from adding further assets declines rapidly towards a level of risk that cannot be further reduced – the 'systematic' risk of the market. Evidence from portfolios of randomly-selected assets shows that almost all of the reduction in non-systematic risk available from portfolio diversification can be achieved by holding as few as 20 shares (Solnik, 1974). Thus although typical ethical investment objectives can rule out significant portions of the market – "the single criterion of avoiding companies paid more than £5m in any one year, from 1984 to 1987, by the British Ministry of Defence would exclude 24.7 per cent of the value of the Financial Times All Share index" Luther et al. (1992) – it is unlikely that diversification of non-systematic risk cannot be achieved in typical ethical portfolios.

Sparkes (2002) remarks that "the anticipation effect should not work as it falls foul of the efficient markets hypothesis". He appears unaware that semi-strong market efficiency also implies that the small companies, anticipation, information and positive selection effects will not deliver superior returns to ethical investors. This is because they all deal with publicly available information to which conventional investors have equal access. If these effects do indeed signal sources of superior investment returns, conventional investors should be equally able to note this and to benefit from it, leading to no difference in performance between ethical and conventional funds.

However, in a world where information collection and processing is costly, views on which subsets of 'all publicly available information' are worthy of consideration - and skills relating to the processing of this information - can reasonably differ. This is a possible source of 'competitive advantage' as referred to above. According to Sparkes (2002, p.274) "Repeated surveys show that financial analysts working in the City of London have little interest in environmental or social factors". Sparkes argues that this is currently a possible source of superior performance by ethical funds, adding that

> *...if SRI methods become generally accepted on the basis that they can produce higher returns then they wil be increasingly adopted, and these excess returns are likely to be arbitraged away (Sparkes, 2000, p.274).*

The above provides a summary of the main theoretical arguments relating to possible sources of over- or under-performance by ethical funds relative to the market expected equilibrium and to similar conventional funds. The remainder of the present research is concerned with the empirical question of whether any such over- or under-performance is observable.

2.6 Chapter Conclusions

The dominant strand of ethical investment fund performance research, to which the present research is a contribution, was begun by Luther et al. (1992).

Early research used market indices as a benchmark for ethical fund performance. Benchmark choice has been considered problematic, and models combining more than one index have been proposed (Luther and Matatko, 1994; Gregory et al., 1997; Cummings 2000). More recently Bauer et al. (2002, 2003a, 2003b) have claimed to "solve the benchmark problem" using a four-factor model.

The present research uses a single factor market model, dealing with concerns regarding benchmark choice by comparing each fund to its own nominated index.

Almost all researchers have used the capital asset pricing model (CAPM) or variations on this. The present research differs, using the market model in preference to the CAPM, for reasons explained in section 5.2.3 on p.64.

Comparison of ethical funds with non-ethical funds was first done by Hamilton et al. (1993), but is often accredited to Mallin et al. (1995) who produced 'matched pairs' based on fund size and age. Subsequent researchers have added further matching criteria (Gregory et al., 1997) and matched with more than one non-ethical fund (Statman, 2000). The present research develops this further, allocating between 3 and 19 non-ethical peers to each ethical fund according to consistently-applied criteria.

Possible timing ability was first accounted for in ethical investment performance research by Kreander et al. (2005) using the Henriksson and Merton (1981) technique. The present research adopts this and also adds a second timing specification proposed by Treynor and Mazuy (1966), selecting whichever (if either) best fits the data.

Kreander et al. (2005) deal with heteroscedasticity by use of Newey and West (1987) 'robust' standard errors and p-values. The present research takes an alternative approach, explicitly modelling the heteroscedasticity. This is a main novel feature of the present research.

The overall conclusion regarding ethical investment performance arising from previous research is that ethical investments perform very similarly to non-ethical investments, with no premium or penalty associated with ethical investment (subject to various detailed caveats).

The previous conclusion relates to the mean level of returns. The present research appears to be novel in explicitly modelling and comparing the <u>variability</u> of the returns of ethical funds (and similar non-ethical funds).

Kreander et al. (2005) appear to be unique in this field in their use of weekly as opposed to monthly data. Unfortunately the present research uses monthly data in common with other previous research; higher frequency data would have been advantageous.

Reasonable theoretical arguments can be put forward in support of ethical fund performance being inferior, superior, or the same as conventional funds or as the market equilibrium level.

This completes the review of relevant literature i.e. literature investigating the financial performance of ethical funds. Reference is made to other publications below in context as the need arises, for example publications detailing particular regression modelling approaches are discussed in chapter 5 Methods of Analysis on p.60.

3. Data I: Family Charities Ethical (FCE*)

3.1 Chapter Overview

This chapter describes fund Family Charities Ethical (FCE*) which is unique (so far as is known) in that it was initially launched in March-82 with conventional financial investment criteria and later 'switched' to ethical investment in March-96, providing a rare opportunity to examine the effect, if any, of this change. There was also a change in fund management in Sept-97, making it necessary to distinguish clearly between these two possible influences on fund performance. A brief history of FCE* is provided in section 3.2.

There follows in section 3.3 on p.29 an allocation of 'peers' – conventional funds that are similar in defined ways, but that do not employ ethical investment criteria. The way in which peers are selected is an important feature of this research.

Section 3.4 Financial Performance Data on p.31 describes the data used in the analysis of FCE* and the selected peers.

Section 3.5 concludes this chapter.

Prior research on FCE*, on which the present research builds, was recently published as Mill (2006) which is provided as Appendix B on p.220.

This is the first of two Data Selection chapters reflecting the fact that the thesis is in two distinct but related parts.

This 3rd chapter - Data I - deals with data selection for fund FCE* with the ensuing results presented in chapter 6, Analysis I: Family Charities Ethical (FCE*) on p.89.

The next, 4th chapter - Data II: Twelve Ethical Funds on p.34 – introduces a further 12 ethical funds and their peers. The results of the analysis of these 12 funds are presented in chapter 7, Analysis II: Twelve Ethical Funds on p.108.

3.2 Introduction to Family Charities Ethical (FCE*)

Family Charities Ethical Trust was launched in March-82 as The Mencap Unit Trust, later changing name to United Charities Trust and then to the current name in 1997. A number of charities invest in the fund, and private investors can opt to covenant their investment income to one of these.

The investment objective of FCE* was initially

> *consistent long term growth of both income and capital*

from a portfolio that

> *may include a proportion of overseas investments (FCIM, 1993).*

UK equities have typically formed between 80% and 90% of FCE* portfolio value.

In March-96 a statement of ethical investment criteria was added:

> *...whilst avoiding investments in companies which generate significant turnover from alcohol or tobacco or which manufacture weapons, supply ozone depleting chemicals, test cosmetics or toiletries on animals, or use significant quantities of tropical hardwood.*

Further additions followed in Sept-96:

> *...using intensive farming methods... trade in prohibited pesticides... activities which significantly pollute waterways... company groups who have registered companies in a significant number of countries identified as violating human rights...*

The statement on weapons manufacture was amended to *"export of goods or military services for military users"*, and use of tropical hardwood was amended to *"extracting or importing tropical hardwood"*.

No changes in investment objectives have occurred since 1996. However in Sept-97 there was a change in fund management that may have influenced fund performance, which is also examined in the analysis below.

It is notable that FCE*'s ethical investment criteria mention avoiding companies with "significant turnover" but do not quantify what will be considered as "significant". Nonetheless, the adoption of ethical investment criteria does appear to have impacted on fund management practice. This can be seen by examining the proceeds from sales of investments (company shares) as a percentage of total investments in the 12 months to 31 March each year, shown in Figure 3-1.

In Figure 3-1 ethical investment criteria adoption in March-96 is indicated by the first of two broken vertical lines (the second vertical line in September-97 relates to the change in fund management, discussed further in chapter 6 on p.89).

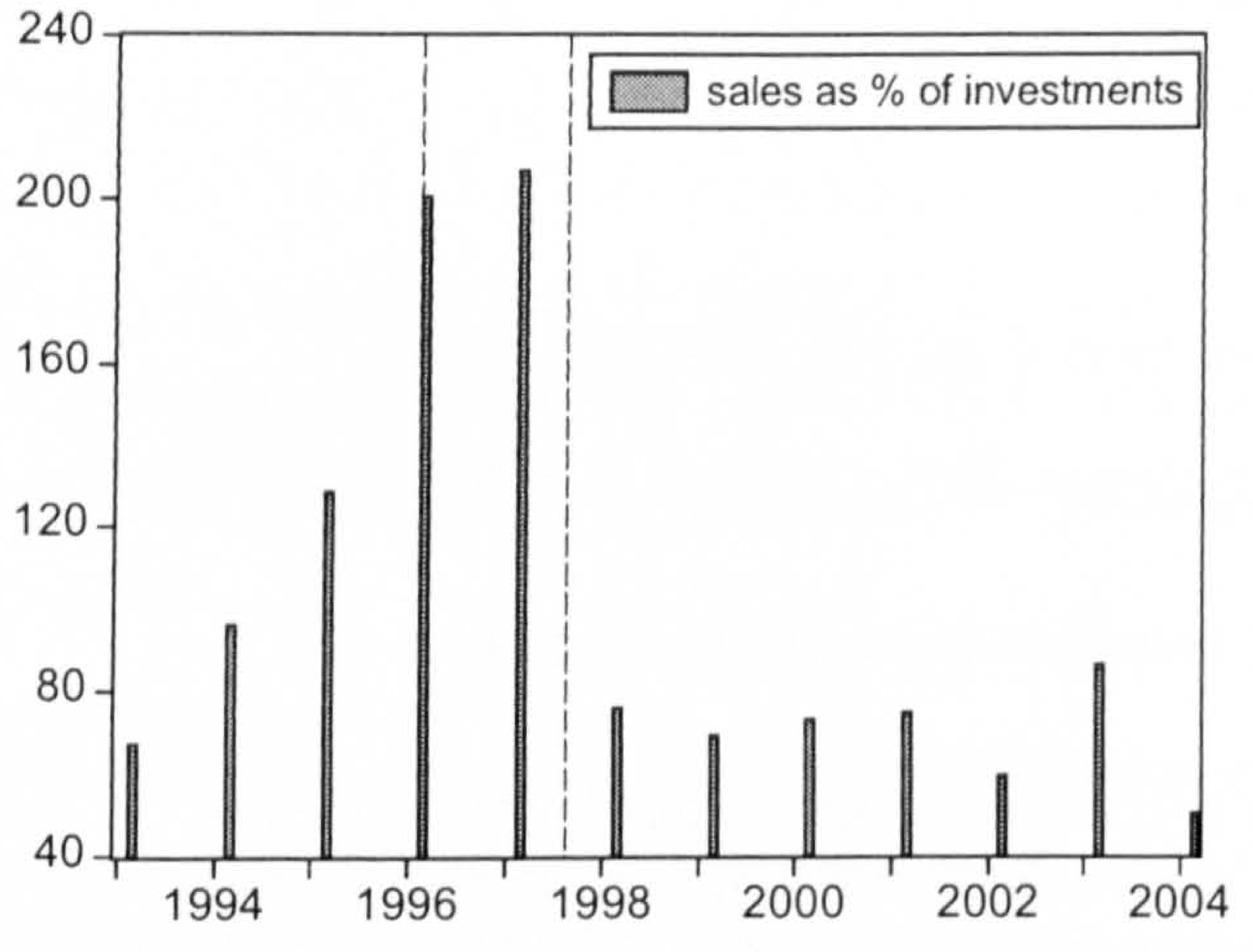

Figure 3-1 Annual proceeds from sales of investments as a percentage of investments at market value for fund FCE*

Figure 3-1 shows that in the two years to March-96 and March-97 (leading up to and just subsequent to the March-96 introduction of ethical investment) sales of investments were around twice the typical level for this fund (generally around 60% to 100% of portfolio value). That these increased sales represent a realignment rather than a reduction of portfolio holdings is indicated by the year-on-year increase in total (nominal) portfolio value between 1995 and 2000 resulting in a seven-fold increase overall.

In the year to March-96 sales of shares in 12 companies, amounting to 46.4% of total portfolio value, can be linked to criteria in the new ethical investment principles: McBride (6.1%, personal care products), Smiths Industries (5.8%, aerospace engineering), Morland (4.5%, brewer), Allied Domecq (4.3%, alcohol retailer), Kwik Save (4.1%, alcohol and tobacco retailer), ML Laboratories (3.6%, pharmaceutical development), T&N (3.6%, infamous asbestos processors), IMI (3.4%, alcohol dispensers), MacDonald Hotels (3.2%, alcohol retailers), Pliva DD (3.0%, pharmaceuticals and cosmetics), Victrex (2.6%, chemicals, aerospace), Greenalls (2.2%, brewer). It may be that individually some of these companies would have been sold for purely financial reasons in the absence of the change in investment objectives, but it is notable that taken together they comprise around half of investment sales in a year in which total investment sales are around twice the typical level.

Major additions to FCE*'s portfolio in 1996 and 1997 included British Biotech (6.4% of portfolio value, biotechnology), Glaxo Wellcome (5.6%, pharmaceutical and healthcare), Platignum (5.2%, pen manufacturer), Abbey National (4.7%, banking), Cantab Pharmaceuticals (4.5%, vaccines and biotechnology), National Grid Group (4.2%, electricity transmission).

Similar Information on changes in the composition of the conventional funds with which FCE* is compared ('peers') was not available. It is hoped that use of a number of 'peer' control funds makes it unlikely that all of the peers underwent similar confounding portfolio changes over the relevant period of time.

3.3 Selection of FCE* Peers

As noted in section 2.4 on p.10, previous UK studies of ethical investment performance have adopted a "matched pair" approach whereby an ethical fund is matched with a <u>single</u> 'similar' conventional fund, following Mallin et al. (1995).

However, it is doubtful whether a single conventional fund can be accurately identified as the unique best standard of comparison for each ethical fund as implied by the term "matched pair". In any case given that in the UK there are over 2000 unit trusts and OEICs of which 90 were ethical as at Jan-07 (Eiris, 2007) the "matched pair" approach is unnecessarily restrictive.

The approach taken here is to seek comparison of an ethical fund with as many conventional peer funds as meet simple matching criteria in terms of fund type (investment sector and benchmark), launch date, and fund size:

1. (Type) Peer funds describe themselves are having either the same benchmark index or the same investment sector as the ethical fund (or both).

2. (Launch date) Peers have a launch date within two years either way of the ethical fund.

3. (Size) Peers are:
   <u>either</u> within +/- 50% of ethical fund size
   <u>or</u> (if this yields less than four peers) the four nearest in size are selected.

Table 3-1 below presents information on these selection criteria (benchmark index, investment sector, launch date, size) for ethical fund FCE* and the four peers that these criteria identify. Also shown is the SEDOL (Stock Exchange Daily Official List) number uniquely identifying each fund, and the three-letter abbreviated label used for convenience in the analysis that follows.

Comparing Table 3-1 with previous research in Mill (2006) (see Appendix E on p. 346), note that the present research increases the number of FCE* peers considered from three to four.

Table 3-1 Ethical fund FCE* (shaded) and conventional peers

fund (sedol number)	label	benchmark	sector	launch	size £m
Family Charities Ethical (57826)	FCE*	FTSE All Share	UK All Companies	May-82	10.0
Solus UK Growth (693886)	SUG	FTSE All Share	UK All Companies	Sep-81	8.9
ISIS UK Growth & Income (577612)	IUG	FTSE All Share	UK All Companies	Jul-83	22.2
Martin Currie IF Income (3156030)	MCI	FTSE All Share	UK Equity Income	Sep-83	28.5
Abbey Assets & Earnings (2653)	AAE	FTSE All Share	UK All Companies	Nov-82	51.8

FCE* can be seen in Table 3-1 to be relatively tiny at only £10 million in May 2001 (the average unit trust size at this time was £142m for UK unit trusts as a whole and £252m for unit trusts with FTSE All-Share index as benchmark). While it will be seen in the next chapter that the +/-50% of ethical fund size criterion is suitable for larger ethical funds, in the case of the very small FCE* this selects only a single peer: Solus UK Growth (SUG). Therefore the four conventional funds nearest in size (and meeting the other selection criteria) are selected, giving SUG, IUG, MCI and AAE.

In addition to the four peers shown in Table 3-1 fund Friends Provident UK Focus also met the selection criteria, with a size of £36.8m. If selected, this would have displaced Abbey Assets & Earnings (AAE) as the fourth peer. However, Friends Provident UK Focus was merged with two other funds to become Friends Provident UK Equity OEIC, which then became ISIS UK Equity OEIC. Such merging of funds confounds the analysis, so Friends Provident UK Focus was not selected, leaving Abbey Assets & Earnings (AAE) as the fourth peer.

The next closest matches with respect to fund size (also meeting the other criteria), would be Canlife High Income (£75m) and AEGON UK Tactical (£85.6m). Clearly, it is not possible to select more than four peers for FCE* without selecting funds that are many times larger than FCE*'s size of £10m (fourth peer AAE is already five times as large as FCE*).

The peers' statements of investment objectives are typically rather brief in comparison to that of FCE* (see p.26). For example, SUG aims for "long-term capital growth through a wide spread of primarily UK quoted securities" (Solus, 2004) while IUG "focuses on achieving medium to long-term capital growth and a high level of income through investment primarily in UK equities" (ISIS, 2004). MCI has stated objective "to produce a rising income combined with capital growth through investment mainly in the United Kingdom... Investment will be in a mixture of ordinary shares, fixed interest and convertible stocks mainly in the UK" (Martin Currie Ltd., 2004).

3.4 Financial Performance Data

The measure of fund performance used is percentage change in nominal bid price from month end to month end with gross dividend income reinvested, from Reuters Hindsight financial database. This takes the form of a total return index provided from this database. Data runs from the launch of FCE* in May-82 (or from launch of the control, if later) until Mar-04.

Figure 3-2 shows monthly returns for FCE*. Adoption of ethical investment objectives in March-96 is shown by the shaded area to the right. Visual inspection alone reveals no immediately apparent trend or change in performance, but of course detailed analysis is required. This is pursued in chapter 6, Analysis I: Family Charities Ethical, from p.89 onwards.

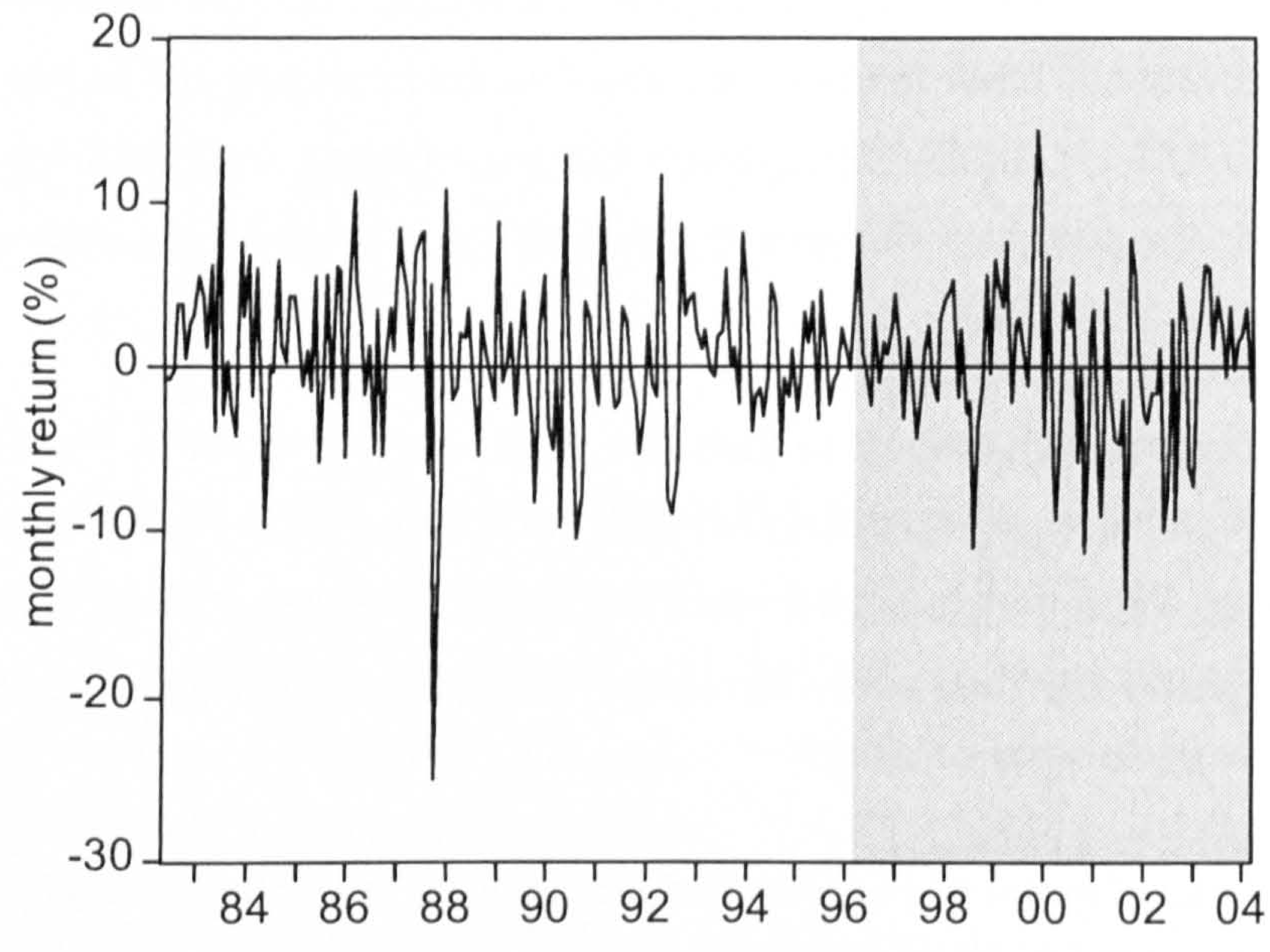

Figure 3-2 Monthly returns (%) for FCE*

The monthly return to an appropriate market index is also required in order to implement the market model that is used in the analysis that follows. All funds in Table 3-1 on p.30 above have the FTSE All Share index as benchmark and the relevant data was again obtained from Reuters Hindsight.

3.5 Chapter Conclusions

An unusual ethical fund – Family Charities Ethical (FCE*) – has been described (section 3.2 on p.26). Unlike all other ethical funds, so far as is known, FCE* was initially launched with conventional investment objectives and 'switched' to ethical investment a number of years later, providing a rare opportunity to examine the effect, if any, of this change. There was an increase in turnover of shareholdings around the time of the change in investment objectives, presumably to achieve realignment with the new objectives.

FCE*'s performance is to be compared with that of similar funds following conventional financial investment criteria i.e. with no additional ethical criteria. The selection of four such peer funds according to fund type (benchmark and investment sector), launch date and size criteria has been described (section 3.3 on p.29).

The analysis of this data is described in chapter 6, Analysis I: Family Charities Ethical (FCE*) on p.89.

Prior research on FCE*, on which the present research builds, was recently published as Mill (2006) which is provided as Appendix B on p.220.

4. Data II: Twelve Ethical Funds

4.1 Chapter Overview

This chapter describes the selection and organisation of data for the dozen UK ethical funds for which the longest series of data were available.

In section 4.2 the types of financial data used are described.

In section 4.3 on p.35 the dozen ethical funds are introduced along with the information that is later used to select peers.

In section 4.4 on p.38 the distinctive ethical investment objectives of each ethical fund are presented, demonstrating some broad similarity but also many differences of detail. In particular, fund Framlington Health (FRA*) has investment objectives quite unlike those of the other ethical funds with which it is generally listed. Also Jupiter Ecology (JUP*) has distinct objectives.

Section 4.5 on p.45 deals with the selection of peer funds for each of the dozen ethical funds, based upon consistent application of the same selection criteria as were used for fund FCE* in the previous chapter.

Having identified 12 ethical funds with varying numbers of peers (from 4 up to 19), giving 118 funds in total with varying start dates, a balance is required to be struck between making full use of the available data for each individual fund and making inter-fund comparisons on a like-for-like basis. The question of how best to strike this balance is addressed in section 4.6 Selection of time samples on p.51.

Section 4.7 on p.59 concludes this chapter, and concludes the selection and description of data.

4.2 Financial Performance Data

In a similar manner to FCE* as described in section 3.4 on p.31, the relevant financial performance data was obtained from the Reuters Hindsight database. Similarly to FCE* and peers, the measure of fund performance used is percentage change in nominal bid price from month end to month end with gross dividend income reinvested, as provided by the database as a total return index for each individual fund.

The monthly return to an appropriate market index is also required. Whereas FCE* and peers (in the previous chapter) all had the FTSE All Share index as benchmark, the dozen ethical funds introduced in this chapter also include two funds with the Hoare Govett smaller companies index as benchmark, and five with the FTSE World index as benchmark (see Table 4-2 on p.36). The peers of these dozen ethical funds include funds with a number of other benchmarks also: FTSE 100, FTSE 350, FTSE World – World, FTSE World – UK, FTSE World – World Ex UK, FTSE Investment Companies and MSCI World.

Implementation of one of the models used in what follows (the capital asset pricing model) also requires a measure of the return to a 'risk free' asset. For this the UK treasury bill one month rate was used, again from Reuters Hindsight.

In all instances, data is considered from the earliest relevant date until July 2004.

4.3 Ethical Funds Considered

The dozen longest established UK ethical funds for which full data was available in the Reuters Hindsight database are listed in Table 4-1.

Table 4-1 Ethical Funds Analysed (With Abbreviated Labels)

Label	Fund Name	Sedol	Launch	Obs to Jul-04
ISG*	ISIS Stewardship Growth	3083451	Jun-84	242
FRA*	Framlington Health	575371	Apr-87	207
SWE*	Scottish Widows Ethical	3220021	Sep-87	201
FPS*	Friends Provident Stewardship Income	5083569	Oct-87	201
AAM*	Allchurches Amity	937131	Feb-88	197
JUP*	Jupiter Ecology Fund	581215	Mar-88	195
CFE*	City Financial Ethical (Acorn)	3064780	Dec-88	186
AEG*	Aegon Ethical	745248	Apr-89	173
SET*	Sovereign Ethical	831761	May-89	181
IIE*	Insight Investment Evergreen	847810	Feb-90	173
ENV*	CIS Environ	161510	May-90	170
HGG*	Henderson Global Care Growth	502722	Aug-91	156

In Table 4-1 the fund name is shown along with its unique Stock Exchange Daily Official List (Sedol) number assigned by the London Stock Exchange. For convenience each fund is assigned a three-letter abbreviated label that is used in what follows. Ethical funds (as these all are) are denoted by an asterisk. The UK's first ethical unit trust, here labelled ISG*, can be seen to have been launched in June 1984

The final column in Table 4-1 shows the number of monthly observations available from the Reuters Hindsight database for each fund up to July 2004. With a data end date of July 2004 the oldest ethical fund ISG* has 242 available monthly observations. Although by Jan-07 there were 90 retail ethical funds in the UK (Eiris, 2007) a large majority of these have been launched relatively recently. Given the use here of monthly data, the number of observations available for the more recently launched funds is too few for reliable analysis. The minimum number of observations considered here is 156, for fund HGG*.

Table 4-1 illustrates some idiosyncrasies of the data. The Hindsight database does not always provide data from the stated month of fund launch, for example SWE* and FPS* have launch dates of Sep-87 and Oct-87, respectively, but in both cases data begins in Nov-97, providing 201 monthly observations for each. In a more extreme case, whereas AEG* was launched in Apr-89 Hindsight data is available only from Mar-90 providing 173 observations rather than the expected 184.

Despite having 'ethicalness' in common, these 12 ethical funds are in fact quite diverse as illustrated in Table 4-2.

Table 4-2 Size, Investment Sector and Benchmark of Ethical Funds Analysed

Fund	Launch	Size (£m)	Sector	Benchmark
ISG*	Jun-84	606.1	UK All Companies	Hoare Govett
FRA*	Apr-87	345.0	Specialist	FTSE World
SWE*	Sep-87	53.5	UK All Companies	Hoare Govett
FPS*	Oct-87	76.1	UK Equity Income	FTSE All Share
AAM*	Feb-88	36.9	UK All Companies	FTSE All Share
JUP*	Mar-88	164.4	Global Growth	FTSE World
CFE*	Dec-88	2.9	Global Growth	FTSE World
AEG*	Apr-89	55.1	UK All Companies	FTSE All Share
SET*	May-89	43.7	UK All Companies	FTSE All Share
IIE*	Feb-90	22.5	Global Growth	FTSE World
ENV*	May-90	153.5	Global Growth	FTSE All Share
HGG*	Aug-91	190.8	Global Growth	FTSE World

In addition to launch date, Table 4-2 provides information on the size of each ethical fund (money under management at the end of May 2001) and the investment sector as supplied by the Reuters Hindsight database. Note that these ethical funds differ in the extent to which they focus on the UK market or have a more international investment focus.

Note also that fund FRA*, Framlington Health, is alone in being listed as 'Specialist'. Although commonly listed amongst ethical investment funds, as shown in section 4.4.2 on p.39 FRA* invests in healthcare and medical companies worldwide – quite different from the investment objectives of the other ethical funds listed, as described in the next section.

Each fund also has a stated benchmark index, either the familiar FTSE All Share index, or the FTSE World index, or the Hoare Govett index. The latter is a specialist smaller companies index published by Hoare Govett Ltd (strictly, Hoare Gov SC(-IT) is used here, i.e. smaller companies excluding the IT sector). Use of this index in the analysis of ethical funds was recommended by Luther and Matatko (1994) and Gregory et al. (1997), as discussed in section 2.4.1 on p.10, as a result of the tendency for ethical funds to be invested in smaller companies.

Each of these: launch date, fund size, investment sector and benchmark, are salient pieces of public information in describing what a fund 'is like'. But there are some subtleties or idiosyncrasies. For example, the tendency to invest in smaller companies is likely to apply to all ethical funds, yet only two of the six UK-focussed funds have a smaller company index (Hoare Govett) as benchmark. Also, while most "Global Growth" funds have a correspondingly international benchmark (FTSE World), ENV*, with the UK FTSE All Share index, does not.

Such simple observations suggest that it is unlikely that the information in Table 4-2 (and similar information for candidate peer funds) provides so accurate a summary of a fund's characteristics that it can be used to identify a unique best non-ethical partner fund to form a "matched pair" as was done by Mallin et al. (1995) (using even less information: fund age and fund size only). It therefore seems reasonable, as was done for fund FCE* in the previous chapter, to identify a group of peers for each ethical fund rather than to rely on accurately identifying a single "matched" peer. This is done in section 4.5 on p.45.

But before turning to the peers, in the next section the investment objectives of each ethical fund are described.

4.4 Ethical Fund Investment Objectives

Each of the 12 ethical funds has a statement of investment objectives specifying non-financial criteria that will be used in the selection of investments, in line with Cowton's (1994) general definition of ethical investment in section 2.2 on p.4.

4.4.1 ISG* ISIS Stewardship Growth Investment Objectives

ISG* is the oldest ethical fund in the UK and one of two 'Stewardship' funds considered here, the other being FPS* (see section 4.4.4 below). It is important to note that "while all the Stewardship funds have the same ethical approach, they vary in where they invest both in terms of geography and investment objectives. Their risk profiles are therefore different" (Friends Provident, undated).

ISG* itself is described:

> *The fund offers you the opportunity to invest in UK shares chosen on ethical grounds as well as for financial gain. The emphasis is on achieving longer-term capital growth, with an increasing income. We reinvest any income in the fund to increase the value of the units (Friends Provident, 2006a).*

The 'Stewardship' approach common to ISG* and FPS* is quite extensively documented; a concise summary of the Stewardship funds' aims is reproduced here (Friends Provident Life and Pensions Ltd, 2006).

Positively view companies that

- *supply the basic necessities of life e.g. health food, clothing, water and housing*
- *provide high quality products and services which are of long term benefit to the community e.g. fair trade of locally sourced products, renewable energy, education and training*
- *conserve energy or natural resources e.g. by sourcing from renewable sources or companies involved in water-saving technologies*
- *have good relations with customers and suppliers*
- *have good employment practices e.g. in equal opportunities and diversity, professional development, rewards, participation and consultation*
- *have good practices in human rights e.g. support international human rights conventions and supply chain labour standards*
- *have good practices in anti-corruption*
- *show strong community relations e.g. donations to charity, employee volunteering, community consultation*

Negatively view companies that

- *own or operate nuclear power stations*
- *manufacture or sell weapons*

- *cause environmental damage / pollution e.g. significantly contribute to and do not tackle climate change, destroy forests, manufacture PVC or endocrine disrupting chemicals, manufacture GM crops or seeds*
- *have poor practices towards customers, suppliers or communities e.g. irresponsible marketing of breast-milk substitutes or pesticides in emerging markets or poor community relations.*
- *have poor employee management e.g. discriminate, have poor health and safety*
- *have poor practices in human rights e.g. perpetrate human rights abuses, facilitate human rights abuses through significant links to an oppressive regime*
- *trade with or have operations that sustain or support repressive regimes*
- *gambling*
- *produce pornography, harmful or offensive material*
- *produce tobacco or alcohol products*
- *unnecessarily exploit animals.*

4.4.2 FRA* Framlington Health Investment Objectives

These are stated as follows:

> *Framlington Health Fund aims to achieve capital growth through investment in health care companies worldwide. The fund's emphasis is on companies that are providing innovative products or solutions for unmet medical needs. We regard this as adopting a positive ethical stance, although investors should be aware that pharmaceutical companies are required by law to test their products on animals before entering human clinical trials (EIRIS, 1998).*

While it may be true that this is "adopting a positive ethical stance" such a stance is markedly at odds with that of other ethical funds with which FRA* is commonly listed. Of the 11 other ethical funds considered here, four (SWE*, CFE, AEG* and IIE*) have a strong statement against investment in companies involved in animal testing and a further three (AAM*, SET* and ENV*) invest in companies involved in animal testing only under restricted conditions.

Since FRA* is the most extreme example of the lack of homogeneity amongst ethical investment funds, it is of interest to discover, given that FRA* invests in different companies to the other ethical funds, whether its financial performance is noticeably different. This is indeed what is found in section 7.3 on p.118 with respect to the variance of FRA* about the benchmark index (which is much higher i.e. 'worse' than the other ethical funds) but not with respect to its (risk-adjusted) mean financial return. FRA*'s distinct financial performance is therefore not discoverable using the techniques employed by previous researchers in this field. (The precise meaning and measurement of these financial performance terms is described in the next chapter dealing with methods of analysis).

4.4.3 SWE* Scottish Widows Ethical Investment Objectives

These are stated as follows:

> *The fund aims to achieve long-term growth by investing in companies with positive ethical practices. Stock selection is based on a screening process using criteria agreed between Scottish Widows Investment Partnership and an independent advisory body. Investment will be mainly in UK company shares. For example the fund's investments might include companies which have a high proportion of their turnover coming from safety equipment, healthcare or environmental technology, or which are active in the community. Companies that are likely to be excluded are those, for example, which produce alcohol or tobacco, provide animal testing services or those which own or operate nuclear power stations (Scottish Widows, 2007).*

The vagueness of the language is of note: "might include", "are likely to be excluded".

4.4.4 FPS* Friends Provident Stewardship Income Investment Objectives

Recall from discussion of ISG* in section 4.4.1 above that "while all the Stewardship funds have the same ethical approach, they vary in where they invest both in terms of geography and investment objectives. Their risk profiles are therefore different" (Friends Provident, undated).

FPS* itself is described:

> *The fund offers you the opportunity to invest in UK shares chosen on ethical grounds as well as for financial gain. The aim is to achieve an above-average income with the prospect of longer-term capital growth. We reinvest any income in the fund to increase the value of the units (Friends Provident, 2006b).*

while its ethical approach is identical to ISG*, described in section 4.4.1 above.

4.4.5 AAM* Allchurches Amity Investment Objectives

These are stated as follows:

> *The Investment Objective of the Allchurches Amity Fund is to provide long term capital appreciation and a reasonable level of income. It seeks to invest in companies which make a positive contribution to the quality of individual and community life and to the environment. The Fund will invest principally in*

> *companies incorporated and/or listed in the United Kingdom. The Fund seeks to avoid investment in companies which have a material involvement in the production of alcohol and the Fund also avoids companies with material interests in tobacco; gambling; the production of magazines or other media of an explicit or violent nature; the manufacturing of armaments; countries which threaten the individual's right to liberty; and companies where animals are experimented on for cosmetic purposes (Ecclesiastical Insurance Group, 2007).*

It becomes apparent in section 7.6 on p.134 that AAM* has outstandingly good financial performance in terms of both risk-adjusted mean return and variance about the benchmark index (again, these terms as used here are defined precisely below).

4.4.6 JUP* Jupiter Ecology Fund Investment Objectives

These are stated as follows:

> *The objective of the Fund is to achieve long-term capital appreciation together with a growing income consistent with a policy of protecting the environment. The Fund's investment policy is to invest worldwide in companies which demonstrate a positive commitment to the long-term protection of the environment (Jupiter International Group, 2006).*

The investment objectives of JUP* are quite distinct from those of the other 12 ethical funds considered here, as JUP* mentions only 'environmental' selection criteria. There is no mention, for example, of the avoidance of companies with interests in tobacco that is common to all the other ethical funds considered here (FRA* does not state tobacco avoidance explicitly in section 4.4.2 above on p.39, but this is implied since its particular investment focus is elsewhere).

It is of interest, therefore, that the financial performance of JUP* is also quite distinct, as it is the only ethical fund with mean risk-adjusted performance significantly better than similar non-ethical funds (see summary in Table 7-25 on p.168; detailed JUP* results are in section 7.7 on p.138).

4.4.7 CFE* City Financial Ethical (Acorn) Investment Objectives

These are stated as follows:

> *The objective of the investment policy is to achieve capital growth from a portfolio of securities excluding investment in companies manufacturing or distributing arms and armaments, tobacco and alcoholic products and drugs; companies participating in animal experiments for research and development of their products; and companies based in oppressive regimes (EIRIS, 1998).*

4.4.8 AEG* Aegon Ethical Investment Objectives

These are stated as follows:

The primary investment objective is to maximise total return by investment in equities and equity type securities in companies based in the UK, principally conducting business in the UK or listed on the UK stock market which meet the fund's predefined ethical criteria (Aegon Asset Management, 2007a).

The funds do not invest in companies that:

- *provide animal testing services or manufacture or sell animal-tested cosmetics or pharmaceuticals.*
- *have any involvement in intensive farming.*
- *operate abattoirs or slaughterhouse facilities.*
- *are producers or retailers of meat, poultry, fish, dairy products or slaughterhouse by-products.*
- *manufacture armaments, nuclear weapons or associated strategic products.*
- *provide critical services to, or own or operate, nuclear power facilities.*
- *are involved in activities which are considered to be environmentally unsound, specifically covering the areas of PVC, ozone depleting chemicals, hazardous pesticides or which have been convicted of serious pollution offences.*
- *have made political donations of more than £25,000 in the last year.*
- *have patented genes.*
- *have investments in betting shops, casinos or amusement arcades accounting for more than 10% of their total business.*
- *derive more than 10% of their total business through involvement in brewing, distillation or sale of alcoholic drinks.*
- *derive more than 10% of their business from the growing, processing or sale of tobacco products.*
- *provide adult entertainment services.*
- *are corporate or international banks with exposure to large corporate or Third World debt.*
- *operate in countries with poor human rights records, and which have no established management policies on human rights issues (Aegon Asset Management, 2007b).*

4.4.9 SET* Sovereign Ethical Investment Objectives

These are stated as follows:

The fund does not invest in any company:

- *with more than 1% of pre-tax profits from any country with oppressive political, social or employment measures*
- *which produces any type of weapon or which are involved in the production of nuclear weapon systems and their components, the construction of non-civilian facilities at nuclear of other armed forces bases*

- *which has an involvement in the production of alcoholic beverages or tobacco or which earns more than 10% of its profits from the distribution or sale of these products, or which derives more than 10% of its profits from gambling activities*
- *whose activities include nuclear processing or which derives a significant percentage of its profits from involvement with the nuclear industry*
- *which manufactures cosmetics which have been tested on animals; produces any item which contains ingredients obtained from endangered species or manufacture fur coats and similar articles.*

The fund invests in companies:

- *whose products or business activities contribute to the improvement of the environment*
- *which display an awareness of environmental issues and are taking steps to reduce their negative impact on the environment*
- *which are known to be good employers with a sound employment record, including human rights.*
- *which contribute to society generally by supporting local community, national or world-wide projects or charities (EIRIS, 1998).*

4.4.10 IIE* Insight Investment Evergreen Investment Objectives

These are stated as follows:

The Evergreen Fund was launched in February 1990 and aims to achieve long-term capital growth by investing in companies throughout the world that meet a range of ethical criteria. The Fund is 'negatively screened', and invests its portfolio in companies whose products, processes or services contribute to the restoration and renewal of the earth's ecology or to a cleaner and healthier environment.

The Fund seeks to avoid companies that:

- *Produce tobacco products.*
- *Provide gambling services.*
- *Produce or supply armaments or strategic parts of armaments.*
- *Produce or distribute pornography.*
- *Manufacture ozone-depleting chemicals, or manufacture or distribute harmful pesticides.*
- *Harvest or sell unsustainable timber or timber products.*
- *Produce, sell or distribute medical or non-medical products that have been tested on animals.*
- *Produce, sell or distribute fur products.*
- *Produce, process or sell meat products.*
- *Operate in countries with particularly problematic human rights records, without having a sufficient policy and procedure in place.*

In addition, approximately 20% of the Fund is invested in companies that provide environmentally beneficial products and services such as renewable energy (wind, solar, geothermal, wave and tidal power), fuel cells, air *quality/emissions control, energy conservation, natural gas, recycling, waste disposal, drinking water purification and wastewater treatment (Insight Investment Management, undated).*

4.4.11 ENV* CIS Environ Investment Objectives

ENV* was renamed CIS Sustainable Leaders Trust in January 2005 with no change in investment objectives, which are stated as follows.

The Trust invests mainly in the securities of quoted UK companies and the remainder in quoted overseas securities.

The core of the investment portfolio consists of shares in companies involved wholly or in part in the manufacture of products, industrial processes or the provision of services associated with improving the environment and the enhancement of human health and safety.

In addition, investments may be made in companies considered likely to be medium to long-term beneficiaries of changing attitudes towards a cleaner and safer environment, including those seen to be making above-average efforts to minimise environmental damage caused by their activities.

All companies are screened on an environmental basis, so as to exclude any whose operations are thought likely to cause significant damage to the environment.

The Trust avoids investment in any company which has a significant amount of its business in countries where there is substantial disregard for human rights; in tobacco and tobacco-related products; in the manufacture, distribution or sale of products which have predominantly military applications; or in products which involve experiments on animals, except for those conducted for the benefit of human or animal health.

Unless there are exceptional mitigating circumstances, investments in companies involved in the generation of nuclear power are avoided.

Efficient portfolio management techniques are permitted for hedging purposes only. These include the use of financial derivative instruments (Co-operative Insurance Society, 2007).

Note that although the name 'Environ' may give the impression of a particular or sole focus on 'environmental' concerns (as was the case with the Jupiter Ecology fund in section 4.4.6 on p.41 above), in fact the CIS Environ fund also includes in its investment objectives typical broader concerns regarding tobacco, human rights, animal experimentation, etc.

4.4.12 HGG* Henderson Global Care Growth Investment Objectives

These are stated as follows:

> *To achieve above average long term capital growth by investing in a mix of assets including UK and overseas equities and fixed interests stocks. Individual companies are chosen for their social and environmental leadership in the area within which they operate (Henderson Global Investors, 2007a).*

HGG* has extensive social, environmental and ethical criteria encompassing two full A4 pages (not reproduced here). These state positive criteria and avoidance criteria in relation to impact on people, on the environment, and on animals (Henderson Global Investors, 2007b).

4.5 Selection Of Peers For Each Ethical Fund

4.5.1 Matching Criteria

The aim in selecting peers with which to compare the ethical funds listed in Table 4-1 and Table 4-2 (see pages 35 and 36) is to use the information in Table 4-2 to apply consistent criteria across all 2,024 UK unit trusts and OEICs (as at May 2001) to arrive at a reasonable number of peers for each of the dozen ethical funds.

The following three peer fund selection criteria are applied consistently to all 13 ethical funds considered in the thesis (including FCE* - see section 3.3 on p.29)

1. (Type) Peer funds describe themselves are having either the same benchmark index or the same investment sector as the ethical fund (or both).
2. (Launch date) Peers have a launch date within two years either way of the ethical fund.
3. (Size) Peers are:
   either within +/- 50% of ethical fund size
   or (if this yields less than four peers) the four nearest in size are selected.

The amendment to the third criterion is necessary in the case of very small ethical funds that are so unusually small that a +/- 50% size range fails to capture peers. This is the case for fund CFE* which can be seen in Table 4-2 on p.36 to be relatively tiny at only £2.9 million in 2001 (in May 2001 the average unit trust size was £142m for UK unit trusts as a whole and £252m for unit trusts with FTSE All-Share index as benchmark).

4.5.2 Listings of Selected Peers

Table 4-3 to Table 4-14 below show the outcome for each of the dozen ethical funds of allocating peers as described in the previous section. The ethical funds are tabulated in order of launch date and within each table the peer funds are listed in order of launch date.

The peer selection criteria yield a range of numbers of peers, from the minimum of four peers (ISG*, FRA*, CFE*, HGG*) up to 19 peers (SET*, Table 4-11 p.49).

This procedure allocates a unique set of peers to each ethical fund. However, some conventional funds are peer to more than one ethical fund. For example, conventional fund CSA is peer to both ethical fund SWE* (Table 4-5) and AEG* (Table 4-10). Likewise conventional fund SAI is peer to four ethical funds: SWE* (Table 4-5), FPS* (Table 4-6), AEG* (Table 4-10) and SET* (Table 4-11).

Table 4-3 ISG* ISIS Stewardship Growth Peers

Label	Name	Benchmark	Sector	Size	Launch
ISG*	ISIS Stewardship Growth	Hoare Govett	UK All Companies	606.1	Jun-84
JPE	JPMF Premier Equity Growth	FTSE All Share	UK All Companies	771.4	Nov-82
IPU	Invesco Perpetual UK Equity	FTSE All Share	UK All Companies	288.3	Aug-83
SMU	Scottish Mutual UK Equity	FTSE All Share	UK All Companies	289.9	Oct-84
AUG	Aberdeen UK Growth	FTSE All Share	UK All Companies	679.9	Aug-85

Table 4-4 FRA* Framlington Health Peers

Label	Name	Benchmark	Sector	Size	Launch
FRA*	Framlington Health	FTSE World – World	Specialist	345.0	Apr-87
MGG	M&G Global Leaders	FTSE World – World	Global Equity Income	187.4	Apr-85
ATT	AEGON Technology Tactical	FTSE World – World	Technology & Telecoms	193.3	Sep-85
NBA	Newton Balanced	FTSE World – World	Balanced Managed	212.8	Nov-86
FPI	Friends Prov Int'l Growth	FTSE World – World	Global Growth	490.5	Oct-87

Table 4-5 SWE* Scottish Widows Ethical Peers

Label	Name	Benchmark	Sector	Size	Launch
SWE*	Scottish Widows Ethical	Hoare Govett	UK All Companies	53.5	Sep-87
FIV	Five Arrows GI UK Major Cos	FTSE World – UK	UK All Companies	60.5	Jul-86
MLU	Merrill Lynch UK Smaller Cos	Hoare Govett	UK Smaller Companies	62.2	May-87
SWG	Smith & Williamson Growth	FTSE All Share	UK All Companies	37.3	May-87
SOU	Sovereign UK Growth	FTSE All Share	UK All Companies	42.0	May-87
BGI	BGI Smaller Cos	Hoare Govett	UK Smaller Companies	31.2	Jun-87
FLE	Fleming PIC Gth 2000	FTSE All Share	UK All Companies	42.1	Nov-87
CSA	Credit Suisse Alpha Growth Retail	F350	UK All Companies	70.1	Jul-88
DUK	DWS UK Equity Income	FTSE All Share	UK All Companies	60.8	Oct-88
NUS	Norwich UK Smaller Cos	Hoare Govett	UK Smaller Companies	49.5	Apr-89
SAI	Scottish Amicable Eq Income	FTSE All Share	UK All Companies	55.72	May-89

Table 4-6 FPS* Friends Provident Stewardship Income Peers

Label	Name	Benchmark	Sector	Size	Launch
FPS*	Friends Prov Stdship Income	FTSE All Share	UK Equity Income	76.1	Oct-87
AEI	Aberdeen Equity Income	FTSE All Share	UK Equity Income	54.3	Nov-85
FLE	Fleming PIC Gth 2000	FTSE All Share	UK All Companies	42.1	Nov-87
NSM	New Star Maximum Income	FTSE All Share	UK Equity Income	90.4	Apr-88
DGS	Deutsche GlobalSpectrum UK	FTSE All Share	UK All Companies	60.8	Oct-88
IIM	Insight Investment Monthly Income	FTSE All Share	UK Equity & Bond	43.2	Feb-89
NSU	New Star UK Capital Growth	FTSE All Share	UK All Companies	89.3	Apr-89
SAI	Scottish Amicable Equity Income	FTSE All Share	UK All Companies	55.7	May-89

Table 4-7 AAM* Allchurches Amity Peers

Label	Name	Benchmark	Sector	Size	Launch
AAM*	Allchurches Amity A Inc	FTSE All Share	UK All Companies	36.9	Feb-88
SMI	Smith & Williamson Income	FTSE All Share	UK Equity & Bond	27.8	May-87
SIN	Sovereign Income	FTSE All Share	UK Equity Income	33.2	May-87
AUE	AEGON UK Equity Income	FTSE All Share	UK Equity Income	26.1	Jun-87
MSS	MGM Special Situations Growth	FTSE All Share	UK All Companies	25.1	Sep-87
FLE	Fleming PIC Gth 2000	FTSE All Share	UK All Companies	42.1	Nov-87
CUT	Consistent Unit Trust	FTSE All Share	UK All Companies	23.7	Feb-88
MCU	Martin Currie IF UK Growth	FTSE All Share	UK All Companies	23.2	Mar-88
BIE	Bank of Ireland Exempt Equity Value	FTSE All Share	UK All Companies	24.1	Apr-88
SAS	Scottish Amicable Equity Strategy	FTSE All Share	UK All Companies	24.1	Oct-88
IIM	Insight Investment Monthly Income	FTSE All Share	UK Equity & Bond	43.2	Feb-89
RIG	Rathbone Income & Growth	FTSE All Share	UK All Companies	24.5	Oct-89
SWS	Scottish Widows UK Sp Sits	FTSE All Share	UK All Companies	31.5	Oct-89
RUB	Rensburg UK Blue Chip Growth	FTSE All Share	UK All Companies	28.7	Jan-90

Table 4-8 JUP* Jupiter Ecology Fund Peers

Label	Name	Benchmark	Sector	Size	Launch
JUP*	Jupiter Ecology Fund	FTSE World – World	Global Growth	164.4	Mar-88
SMR	Standard Managed Ret	FTSE World - World	Active Managed	97.1	May-86
SIG	Sovereign International Gth	FTSE World – World Ex UK	Global Growth	104.9	May-87
NIG	Newton International Growth	FTSE World – World	Global Growth	96.7	Jun-87
CUO	Cazenove UK Opportunities	FTSE World – World	Balanced Managed	149.9	Oct-88
AXA	AXA Global Growth	FTSE World – World	Global Growth	91.5	Apr-89

Table 4-9 CFE* City Financial Ethical (Acorn) Peers

Label	Name	Benchmark	Sector	Size	Launch
CFE*	City Financial Ethical (Acorn)	FTSE World – World	Global Growth	2.9	Dec-88
MIE	MGM International Eq Growth	FTSE World – World	Global Growth	11.4	Sep-87
BIW	Bank of Ireland Worldwide Opps	FTSE World – World	Global Growth	7.7	Feb-88
MCB	Martin Currie IF Bal P'folio	FTSE World – World	Balanced Managed	13.7	Apr-89
AGG	Artemis Global Growth	MSCI World	Global Growth	10.6	Jun-90

Table 4-10 AEG* Aegon Ethical Peers

Label	Name	Benchmark	Sector	Size	Launch
AEG*	Aegon Ethical	FTSE All Share	UK All Companies	55.1	Apr-89
SWG	Smith & Williamson Growth	FTSE All Share	UK All Companies	37.3	May-87
SOU	Sovereign UK Growth	FTSE All Share	UK All Companies	42.0	May-87
SMI	Smith & Williamson Income	FTSE All Share	UK Equity & Bond	27.8	May-87
SIN	Sovereign Income	FTSE All Share	UK Equity Income	33.2	May-87
FLE	Fleming PIC Gth 2000	FTSE All Share	UK All Companies	42.1	Nov-87
IPR	INV-PERP Rupert Childrens	FTSE 100	UK All Companies	78.1	Apr-88
CSA	Credit Suisse Alpha Growth Retail	FTSE 350	UK All Companies	70.1	Jul-88
DGS	Deutsche GlobalSpectrum UK	FTSE All Share	UK All Companies	60.8	Oct-88
CUO	Cazenove UK Opportunities	FTSE World – World	Balanced Managed	149.9	Oct-88
IIM	Insight Investment Monthly Income	FTSE All Share	UK Equity & Bond	43.2	Feb-89
SAI	Scottish Amicable Equity Income	FTSE All Share	UK All Companies	55.7	May-89
SWS	Scottish Widows UK Sp Sits	FTSE All Share	UK All Companies	31.5	Oct-89
RUB	Rensburg UK Blue Chip Growth	FTSE All Share	UK All Companies	28.7	Jan-90
GAM	GAM UK Diversified	FTSE All Share	UK All Companies	36.3	Aug-90
FAM	Family Asset	FTSE All Share	UK All Companies	65.9	Jan-91

Table 4-11 SET* Sovereign Ethical Peers

Label	Name	Benchmark	Sector	Size	Launch
SET*	Sovereign Ethical	FTSE All Share	UK All Companies	43.7	May-89
SWG	Smith & Williamson Growth	FTSE All Share	UK All Companies	37.3	May-87
SOU	Sovereign UK Growth	FTSE All Share	UK All Companies	42.0	May-87
SMI	Smith & Williamson Income	FTSE All Share	UK Equity & Bond	27.8	May-87
SIN	Sovereign Income	FTSE All Share	UK Equity Income	33.2	May-87
AUE	AEGON UK Equity Income	FTSE All Share	UK Equity Income	26.1	Jun-87
MSS	MGM Special Situations Growth	FTSE All Share	UK All Companies	25.1	Sep-87
FLE	Fleming PIC Gth 2000	FTSE All Share	UK All Companies	42.1	Nov-87
CUT	Consistent Unit Trust	FTSE All Share	UK All Companies	23.7	Feb-88
MCU	Martin Currie IF UK Growth	FTSE All Share	UK All Companies	23.2	Mar-88
BIE	Bank of Ireland Exempt Equity	FTSE All Share	UK All Companies	24.1	Apr-88
DGS	Deutsche GlobalSpectrum UK	FTSE All Share	UK All Companies	60.8	Oct-88
SAS	Scottish Amicable Equity Strategy	FTSE All Share	UK All Companies	24.1	Oct-88
CUO	Cazenove UK Opportunities	FTSE World – World	Balanced Managed	149.9	Oct-88
IIM	Insight Investment Monthly Income	FTSE All Share	UK Equity & Bond	43.2	Feb-89
SAI	Scottish Amicable Equity Income	FTSE All Share	UK All Companies	55.7	May-89
RIG	Rathbone Income & Growth	FTSE All Share	UK All Companies	24.5	Oct-89
SWS	Scottish Widows UK Sp Sits	FTSE All Share	UK All Companies	31.5	Oct-89
RUB	Rensburg UK Blue Chip Growth	FTSE All Share	UK All Companies	28.7	Jan-90
GAM	GAM UK Diversified	FTSE All Share	UK All Companies	36.3	Aug-90

Table 4-12 IIE* Insight Investment Evergreen Peers

Label	Name	Benchmark	Sector	Size	Launch
IIE*	Insight Investment Evergreen	FTSE World – World	Global Growth	22.5	Feb-90
GME	Gartmore PS Managed Eq	FTSE World – World	Global Growth	16.2	Apr-88
MCB	Martin Currie IF Bal P'folio	FTSE World – World	Balanced Managed	13.7	Apr-89
SGE	Schroder Institutional Global	FTSE World – World	Global Growth	14.7	May-89
CFS	CF Stewart Ivory Investment	FTSE Investment Companies	Global Growth	22.6	Sep-89
ABP	AEGON The Balanced P'folio	FTSE World – World	Balanced Managed	19.5	Nov-89
THO	Thornhill American	FTSE World – World	Global Growth	13.8	Jun-90
IIG	Insight Investment Global Eq	FTSE World – World	Global Growth	27.8	Sep-90
SWT	Smith & Williamson	FTSE World – World	Global Growth	23.7	Sep-90
WAY	WAY Global Red Portfolio	FTSE World – World	Active Managed	22.7	Dec-91
EGO	Exeter Global Opportunities	FTSE Investment Companies	Global Growth	15.3	Feb-92

Table 4-13 ENV* CIS Environ Peers

Label	Name	Benchmark	Sector	Size	Launch
ENV*	CIS Environ	FTSE All Share	Global Growth	153.5	May-90
SIO	Schroder Institutional O'seas Eq	FTSE World – World Ex UK	Global Growth	77.2	Jul-88
DGS	Deutsche GlobalSpectrum UK	FTSE All Share	UK All Companies	60.8	Oct-88
CSM	Credit Suisse Monthly Income	FTSE All Share	UK Equity Income	184.7	Feb-89
AXA	AXA Global Growth B	FTSE World – World	Global Growth	91.5	Apr-89
NUE	Norwich UK Equity Income	FTSE All Share	UK Equity Income	139.9	Apr-89
MSU	Marks & Spencer UK Select	FTSE All Share	UK All Companies	155.9	Oct-89
SWU	Scottish Widows UK Eq Growth	FTSE All Share	UK All Companies	153.1	Nov-89
SWI	Scottish Widows UK Eq Income	FTSE All Share	UK Equity Income	87.1	Nov-89
ADG	Abbey Dividend & Growth	FTSE All Share	UK Equity Income	130.3	Dec-89
NII	Norwich Int'l Index Tracking	FTSE World – World Ex UK	Global Growth	175.4	Feb-91
SJP	St James's Place UK Income	FTSE All Share	UK Equity Income	77.15	Jan-92

Table 4-14 HGG* Henderson Global Care Growth Peers

Label	Name	Benchmark	Sector	Size	Launch
HGG*	Henderson Global Care	FTSE World – World	Global Growth	190.8	Aug-91
QGG	Quilter Global Growth	FTSE Investment Companies	Global Growth	69.8	Feb-90
SPO	Schroder Portfolio	FTSE World – World	Balanced Managed	340.6	Aug-90
LGW	Legal & General Worldwide	FTSE World – World	Active Managed	83.0	Oct-90
NII	Norwich Int'l Index Tracking	FTSE World – World Ex UK	Global Growth	175.4	Feb-91

The allocation of peers in Table 4-3 to Table 4-14 is reasonable and consistent, but clearly for a given ethical fund, some peers are a 'closer match' than others, and ideally some indication of the robustness of results to the narrowness or breadth of peer selection is desirable. The next section describes the use of five different 'time samples' over which analysis was repeated. This has the effect of repeating the analysis firstly using all peers listed in the tables above (below this is referred to as time sample 'all'), and then again using only some of the 'closer' peers.

For example, although SAI is allocated as a peer to four ethical funds SWE*, FPS*, AEG* and SET*, the most restrictive time sample ('ind' – explained in the next section) includes SAI in the analysis for AEG* and SET*, but not for SWE* or FPS*. This reflects the fact that the launch date of SAI is very close in time to that of AEG* (one month later) and SET* (the same month) but farther from that of SWE* (20 months later) and FPS* (19 months later).

The notion of 'time samples', as used here, is described fully in the next section.

4.6 Selection of time samples

4.6.1 Guiding considerations

If performance of an ethical fund is estimated over time period X and that of its peer(s) estimated over time period Y (where X and Y overlap significantly but are not identical), the question arises as to whether any observed difference in performance is due to the difference in investment criteria or the difference in time period considered. Comparisons would appear to require analysis over a common time period, as in previous research (see section 2.4 on p.10).

There are also other considerations. Firstly, the 'common time period' approach may not make efficient use of available data. The number of monthly observations available here varies considerably from 242 for ISG* to almost half of this, 127 observations.

Secondly, if a phenomenon such as a difference in the financial performance of an ethical fund relative to its peers genuinely exists, is significant in magnitude, and persists over time – albeit, perhaps, with some variability and amongst a certain amount of random 'noise' – it might be expected to be detected over somewhat different time periods in comparison with somewhat varying reasonable sets of peers. The extent to which this is the case gives some indication of the reliability of the detection of the phenomenon, and of its practical importance, if any.

In order to take account of the above considerations, the data have been analysed over five different 'time samples' - denoted 'all', 'ind', 'x4', 'x8' and 'x12'. In most cases this also has the effect of comparing each ethical fund with a somewhat different set of peers varying in 'closeness' with respect to launch date, as illustrated in Table 4-15 on p.52.

Table 4-15 on p.52 lists ethical funds in order of launch date, each with its peers also listed in order of launch date. Data availability in terms of number of monthly observations for each fund is shown (with explanatory notes in some cases, indicated by superscript letters referring to notes at the end of the table).

The final columns of Table 4-15 indicate whether a given fund is a member of one of the five 'time samples' - 'all', 'ind', 'x4', 'x8' and 'x12'. These and other aspects of Table 4-15 are explained more fully in sections 4.6.2 to 4.6.6 below, starting from p.55, after Table 4-15.

Table 4-15 Time Sample Membership of Ethical Funds and Peers

Label	Name	Launch	Obs	all	ind	x4	x8	x12
ISG*	ISIS Stewardship Growth	Jun-84	242 [a]	•	•	•	•	•
JPE	JPMF Premier Equity Growth	Nov-82	242	•	•	•	•	•
IPU	Invesco Perpetual UK Equity	Aug-83	237	•	•	•	•	•
SMU	Scottish Mutual UK Equity	Oct-84	238	•	•	•	•	•
AUG	Aberdeen UK Growth	Aug-85	227	•	•	•	•	•
FRA*	Framlington Health	Apr-87	207	•	•	•	•	•
MGG	M&G Global Leaders	Apr-85	231 [b]	•	•	•	•	•
ATT	AEGON Technology Tactical	Sep-85	226 [b]	•	•	•	•	•
NBA	Newton Balanced	Nov-86	212 [b]	•	•	•	•	•
FPI	Friends Prov Int'l Growth	Oct-87	176 [e]	•				
SWE*	Scottish Widows Ethical	Sep-87	201	•	•	•	•	•
FIV	Five Arrows GI UK Major Cos	Jul-86	191 [c, e]	•				
MLU	Merrill Lynch UK Smaller Cos	May-87	206	•	•	•	•	•
SWG	Smith & Williamson Growth	May-87	206	•	•	•	•	•
SOU	Sovereign UK Growth	May-87	206	•	•	•	•	•
BGI	BGI Smaller Cos	Jun-87	205	•	•	•	•	•
FLE	Fleming PIC Gth 2000	Nov-87	190 [f]	•				
CSA	Credit Suisse Alpha Growth Retail	Jul-88	193	•			•	•
DUK	DWS UK Equity Income	Oct-88	163 [e]	•				
NUS	Norwich UK Smaller Cos	Apr-89	183	•			•	•
SAI	Scottish Amicable Eq Income	May-89	182	•			•	•
FPS*	Friends Prov Stdship Income	Oct-87	201 [g]	•	•		•	•
AEI	Aberdeen Equity Income	Nov-85	199 [e]	•				
FLE	Fleming PIC Gth 2000	Nov-87	190 [f]	•				
NSM	New Star Maximum Income	Apr-88	195	•	•		•	•
DGS	Deutsche GlobalSpectrum UK	Oct-88	188	•			•	•
IIM	Insight Investment Monthly Income	Feb-89	185	•	•		•	•
NSU	New Star UK Capital Growth	Apr-89	183	•	•		•	•
SAI	Scottish Amicable Equity Income	May-89	182	•			•	•
AAM*	Allchurches Amity A Inc	Feb-88	197 [h]	•	•	•	•	•
SMI	Smith & Williamson Income	May-87	206	•	•	•	•	•
SIN	Sovereign Income	May-87	206	•	•	•	•	•
AUE	AEGON UK Equity Income	Jun-87	180 [e]	•				
MSS	MGM Special Situations Growth	Sep-87	202	•	•	•	•	•
FLE	Fleming PIC Gth 2000	Nov-87	190 [f]	•				
CUT	Consistent Unit Trust	Feb-88	196	•		•	•	•
MCU	Martin Currie IF UK Growth	Mar-88	196	•		•	•	•
BIE	Bank of Ireland Exempt Equity	Apr-88	189	•			•	•
SAS	Scottish Amicable Equity Strategy	Oct-88	189	•			•	•
IIM	Insight Investment Monthly Income	Feb-89	185	•			•	•
RIG	Rathbone Income & Growth	Oct-89	173	•				•
SWS	Scottish Widows UK Sp Sits	Oct-89	150 [i]	•				
RUB	Rensburg UK Blue Chip Growth	Jan-90	173	•				•

continues overleaf…

Table 4-15 Time Sample Membership of Ethical Funds and Peers (continued)

Label	Name	Launch	Obs	all	ind	x4	x8	x12
	...continued from previous page							
JUP*	Jupiter Ecology Fund	Mar-88	195	•	•		•	•
SMR	Standard Managed Ret	May-86	219 [b]	•	•		•	•
SIG	Sovereign International Gth	May-87	206 [d]	•				
NIG	Newton International Growth	Jun-87	205	•	•		•	•
CUO	Cazenove UK Opportunities	Oct-88	176 [j]	•				•
AXA	AXA Global Growth	Apr-89	183	•	•		•	•
CFE*	City Financial Ethical (Acorn)	Dec-88	186	•	•		•	•
MIE	MGM International Eq Growth	Sep-87	202	•	•		•	•
BIW	Bank of Ireland Worldwide Opps	Feb-88	197	•	•		•	•
MCB	Martin Currie IF Bal P'folio	Apr-89	183	•	•		•	•
AGG	Artemis Global Growth	Jun-90	169	•				•
AEG*	Aegon Ethical	Apr-89	173	•	•			•
SWG	Smith & Williamson Growth	May-87	206	•	•			•
SOU	Sovereign UK Growth	May-87	206	•	•			•
SMI	Smith & Williamson Income	May-87	206	•	•			•
SIN	Sovereign Income	May-87	206	•	•			•
FLE	Fleming PIC Gth 2000	Nov-87	190 [f]	•				
IPR	INV-PERP Rupert Childrens	Apr-88	195	•	•			•
CSA	Credit Suisse Alpha Growth Retail	Jul-88	193	•	•			•
DGS	Deutsche GlobalSpectrum UK	Oct-88	188	•	•			•
CUO	Cazenove UK Opportunities	Oct-88	176 [j]	•	•			•
IIM	Insight Investment Monthly Income	Feb-89	185	•	•			•
SAI	Scottish Amicable Equity Income	May-89	182	•	•			•
SWS	Scottish Widows UK Sp Sits	Oct-89	150 [i]	•				
RUB	Rensburg UK Blue Chip Growth	Jan-90	173	•	•			•
GAM	GAM UK Diversified	Aug-90	167	•				•
FAM	Family Asset	Jan-91	161	•				•
SET*	Sovereign Ethical	May-89	181	•	•		•	•
SWG	Smith & Williamson Growth	May-87	206	•	•		•	•
SOU	Sovereign UK Growth	May-87	206	•	•		•	•
SMI	Smith & Williamson Income	May-87	206	•	•		•	•
SIN	Sovereign Income	May-87	206	•	•		•	•
AUE	AEGON UK Equity Income	Jun-87	180 [e]	•				
MSS	MGM Special Situations Growth	Sep-87	202	•	•		•	•
FLE	Fleming PIC Gth 2000	Nov-87	190 [f]	•				
CUT	Consistent Unit Trust	Feb-88	196	•	•		•	•
MCU	Martin Currie IF UK Growth	Mar-88	196	•	•		•	•
BIE	Bank of Ireland Exempt Equity	Apr-88	189	•	•		•	•
DGS	Deutsche GlobalSpectrum UK	Oct-88	188	•	•		•	•
SAS	Scottish Amicable Equity Strategy	Oct-88	189	•	•		•	•
CUO	Cazenove UK Opportunities	Oct-88	176 [j]	•				•
IIM	Insight Investment Monthly Income	Feb-89	185	•	•		•	•
SAI	Scottish Amicable Equity Income	May-89	182	•	•		•	•
RIG	Rathbone Income & Growth	Oct-89	173	•				•
SWS	Scottish Widows UK Sp Sits	Oct-89	150 [i]	•				
RUB	Rensburg UK Blue Chip Growth	Jan-90	173	•				•
GAM	GAM UK Diversified	Aug-90	167	•				•

continues overleaf...

Table 4-15 Time Sample Membership of Ethical Funds and Peers (continued)

Label	Name	Launch	Obs	all	ind	x4	x8	x12
	...continued from previous page							
IIE*	Insight Investment Evergreen	Feb-90	173	•	•			•
GME	Gartmore PS Managed Eq	Apr-88	191 [k]	•				
MCB	Martin Currie IF Bal P'folio	Apr-89	183	•	•			•
SGE	Schroder Institutional Global Equity	May-89	181	•	•			•
CFS	CF Stewart Ivory Investment	Sep-89	145 [l]	•				
ABP	AEGON The Balanced P'folio	Nov-89	173	•	•			•
THO	Thornhill American	Jun-90	169	•				•
IIG	Insight Investment Global Eq	Sep-90	166	•				•
SWT	Smith & Williamson Thoroughbred	Sep-90	166	•				•
WAY	WAY Global Red Portfolio	Dec-91	151	•				
EGO	Exeter Global Opportunities	Feb-92	124	•				
ENV*	CIS Environ	May-90	170	•	•			•
SIO	Schroder Institutional O'seas Eq	Jul-88	192 [d]	•				
DGS	Deutsche GlobalSpectrum UK	Oct-88	188	•	•			•
CSM	Credit Suisse Monthly Income	Feb-89	185	•	•			•
AXA	AXA Global Growth B	Apr-89	183	•	•			•
NUE	Norwich UK Equity Income	Apr-89	183	•	•			•
MSU	Marks & Spencer UK Select	Oct-89	176	•	•			•
SWU	Scottish Widows UK Eq Growth	Nov-89	153 [m]	•				
SWI	Scottish Widows UK Eq Income	Nov-89	153 [m]	•				
ADG	Abbey Dividend & Growth	Dec-89	154 [n]	•				
NII	Norwich Int'l Index Tracking	Feb-91	161 [d]	•				
SJP	St James's Place UK Income	Jan-92	150					
HGG*	Henderson Global Care Growth A	Aug-91	156	•	•			•
QGG	Quilter Global Growth	Feb-90	173	•	•			•
SPO	Schroder Portfolio	Aug-90	166	•	•			•
LGW	Legal & General Worldwide	Oct-90	166	•	•			•
NII	Norwich Int'l Index Tracking	Feb-91	161 [d]	•				

Notes

Note a: Hoare Govett index data are available from Feb-87 giving 210 observations
Note b: FTSE World - World index data are available from Jan-87 giving 211 observations
Note c: FTSE World - UK index data are available from Jan-94 giving 127 observations
Note d: FTSE World – World Ex UK index data are available from Jan-94 giving 127 observations
Note e: data are unavailable after Jun-02
Note f: data are unavailable after Oct-03
Note g: although FPS* is the 4th oldest ethical fund, when taken together with the available peers it does not form the 4th longest run of data and so is not in sample x4 (see text for details)
Note h: although AAM* is the 5th oldest ethical fund, when taken together with the available peers it forms the 4th longest run of data and so AAM* (rather than FPS*) is in sample x4 (see text for details)
Note i: although SWS was launched Oct-89 available data begin Mar-90; also data is unavailable after Sept-02
Note j: although CUO was launched Oct-88 available data begin Dec-89
Note k: data are unavailable after Mar-04
Note l: although CFS was launched Sept-89 available data begin Jul-92
Note m: data are unavailable after Aug-02
Note n: data are unavailable after Oct-02

4.6.2 Time Sample 'all'

At one extreme of a range of possibilities is simply to use all of the data just as it happens to be available for each individual fund. Here this is denoted by time sample 'all'.

Time sample 'all' analyses every one of the 12 ethical funds and peers for which any data are available, over whatever time period the data is available.

In Table 4-15 above membership of a fund in a time sample is indicated by a 'dot' marker in the relevant column. Thus every fund listed has a marker in the column headed 'all'.

However, a brief glance at Table 4-15 shows that the number of monthly observations for each fund varies considerably. Therefore while, in a sense, making use of all of the available data, sample 'all' entirely ignores the concerns in section 4.6.1 on p.51 regarding comparability. Results using time sample 'all' must therefore be treated with caution. But if results from time sample 'all' agree with results common to other time samples, this may be evidence of robustness of the results.

4.6.3 Time Sample 'x12'

Time sample 'x12' runs from Aug-91 to Jul-04 and includes all 12 ethical funds.

At the other extreme to sample 'all', one might select the fund or market index for which data are available over a common time period with the maximum number of other funds and indices, and perform the analysis over this time period. This would ensure comparability in line with comments in section 4.6.1 on p.51, but simply ignores much of the available data.

Taking this approach the latest start date would be Jan-94, the date from which the FTSE World – World Ex UK and FTSE World – UK indices are available. The earliest end date would be Jun-02 after which data for fund FLE (a peer of SWE* and other ethical funds) are no longer available.

Between these two dates there are 102 monthly observations – rather few for the analysis techniques employed here. These constraints bind in only 9 cases, while having a large effect. Only two funds have the FTSE World – UK index as benchmark (FIV, a peer of SWE*; and SIG, a peer of JUP*) and two have the FTSE World – World

Ex UK index as benchmark (SIO, a peer of ENV*; and NII, a peer of ENV* and HGG*). Only 5 funds have no data available after Jun-02: FPI, FIV, DUK, AEI and AUG, peers of FRA*, SWE*, FPS*, AAM* and SET*.

To relax these constraints a little:

sample 'x12' selects the largest common time period over which all 12 ethical funds have full data (including the relevant benchmark index) for at least three of the minimum of four peers selected for each ethical fund.

This expands the number of common observations from 102 to 156.

In Table 4-15 on p.52 some areas are shaded out. This represents instances where the launch date of a peer fund is later than the beginning of a time sample, so the peer fund cannot be in this time sample. For example, looking at ethical fund ENV*, peer SJP has the final column shaded indicating that its launch date of Jan-92 is after the start of time sample 'x12' (Aug-91) so that SJP cannot be included in 'x12'.

Table 4-15 on p.52 also shows a number of other peers meeting the selection criteria in section 4.5 on p.45 that lack the 'dot' marker in the final column of Table 4-15 indicating that the fund is included in 'x12'. Each of these has a letter superscript beside the number of observations, referring to a note explaining why the fund is not a member of 'x12' due to reasons of data availability rather then launch date. For example, funds SWU and SWI have no data after Aug-02 whereas data until Jul-04 is required for inclusion in time sample 'x12'.

4.6.4 Time Sample 'x8'

Time sample 'x8' runs from Jul-89 to Jul-04 and includes eight ethical funds: ISG*, FRA*, SWE*, FPS*, AAM*, JUP*, CFE* and SET*.

Sample 'x8' is the largest common time period over which 8 ethical funds have full data (including the relevant benchmark index) for at least three of the minimum of four peers selected for each ethical fund.

This provides 181 common observations, more than time sample 'x12' but across fewer funds.

In Table 4-15 on p.52 the 'x8' column is entirely shaded for the four ethical funds (and their peers) that are not included in 'x8': AEG*, IIE*, ENV* and HGG*.

Where an ethical fund is a member of time sample 'x8' some of its peers have launch dates later than Jul-89 and so cannot be members of 'x8'; these parts of the column headed x8 in Table 4-15 are shaded out. For example, this is the case for AAM*'s most recently launched three peers RIG, SWS and RUB.

Similarly to 'x12' in the previous section, there are also some funds that lack, in the column headed x8, either a 'dot' marker indicating sample membership or shading indicating a launch date too late. Again, these funds are omitted for reasons of data availability as described in the notes at the bottom of Table 4-15 referenced by the superscript letter beside the relevant number of observations. For example fund FPI, a peer of FRA*, is excluded from sample 'x8' as it lacks data after Jun-02 whereas data until Jul-04 are required.

4.6.5 Time Sample 'x4'

Time sample 'x4' runs from Apr-88 to Jul-04 and includes ethical funds ISG*, FRA*, SWE* and AAM*.

Sample 'x4' is the largest common time period over which <u>4 ethical funds</u> have full data (including the relevant benchmark index) <u>for at least three</u> of the minimum of four peers selected for each ethical fund.

This provides 196 common observations.

Note that ethical funds are listed in Table 4-15 on p.52 in launch date order, and that fund <u>FPS* is not in sample 'x4'</u> (there are no 'dot' markers in the x4 column) despite having an earlier launch date than ethical fund AAM*, which is in 'x4'. This arises because FPS* has no eligible peers. Peers AEI and FLE have data available only until Jun-02 and Oct-03, respectively – not until Jul-04 as required. And the other peers identified by the matching criteria in section 4.5.1 on p.45 have launch dates later than Apr-88 when sample 'x4' begins.

The start dates of samples 'x4', 'x8' and 'x12' were selected so as to provide three samples of funds trading off longevity of data against breadth of cross section.

However, it is a little unfortunate that 'x4', the 'oldest' sample, does not consist of the four earliest-launched ethical funds.

4.6.6 Time Sample 'ind'

Time sample 'ind' includes all 12 ethical funds.

Time sample 'ind' is the largest time period over which an individual ethical fund has data (including the relevant benchmark index) for at least three peers, varied from ethical fund to ethical fund.

Time sample 'ind' is a compromise between the common-sample cross sections 'x4', 'x8', 'x12' and the use of whatever data is available in sample 'all'.

Since, for a given ethical fund, all peers are eligible for consideration for inclusion in time sample 'ind', there is no shading in this column of Table 4-15 on p.52.

4.6.7 Comments Regarding Time Samples

In some instances in Table 4-15 on p.52 the set of peers for an ethical fund varies little from time sample to time sample. This is the case for ethical fund ISG*, for example, which has the same four peers throughout. Variation in ISG* results will be due only to variation in the time period analysed.

In most instances, however, the set of peers changes from time sample to time sample. This is illustrated clearly by fund AAM* whose set of peers expands from 3 in 'ind' to 5 in 'x4', 8 in 'x8', 10 in 'x12' and 13 in 'all'.

When considering the performance of a particular ethical fund, results from time sample 'ind' are perhaps of particular interest as this makes efficient use of the available data and compares with 'closer' peers.

If seeking to make statements about ethical funds in general the results from time samples 'x4', 'x8' and 'x12' provide a reasonable basis for comparisons.

For a given ethical fund, the consistency (or otherwise) of results across all five time samples may provide some indication of reliability of results.

4.7 Chapter Conclusions

This chapter has introduced 12 ethical funds (section 4.3 on p.35) and described the non-financial investment objectives that set them apart as 'ethical' (section 4.4 on p.38).

While all 12 funds clearly accord with Cowton's (1994) definition of ethical investment in section 2.2 on p.4, they are also quite diverse and do not form a homogeneous group. Two ethical funds stand out in particular. The Framlington Health fund (FRA*, section 4.4.2, p.39), has investment objectives that conflict directly with those of four other ethical funds and somewhat less so with a further three. And the Jupiter Ecology fund has investment objectives focussed solely on environmental concerns without traditional broader ethical investment concerns such involvement in tobacco, alcohol, gambling, human rights, animal testing, etc. (JUP*, section 4.4.6 on p.41).

The data used have been described (section 4.2 on p.34).

The main focus of this chapter has been the allocation of 'similar' non-ethical funds with which to compare each ethical fund. The matching criteria used have been described and applied in section 4.5 on p.45 with the results being illustrated in a series of tables.

Decisions have also been made regarding the time periods over which it is reasonable to make comparisons between funds, as described in section 4.6 on p.51. The choice of time period for analysis and comparison also affects the set of peers with which an ethical fund is compared. These related ideas have been dealt with by introducing the notion of a 'time sample'. Five time samples have been defined: 'x4', 'x8', 'x12', 'ind' and 'all'.

Time sample 'ind' makes good use of available data to assess the performance of an individual ethical fund. In seeking to make general statements about ethical funds as a group, results from time samples 'x4', 'x8' and 'x12' are perhaps of more interest. The extent of consistency of results across all five time samples may provide some indication of the 'robustness' or reliability of results.

This concludes the description and preparatory organisation of the data. The next chapter considers how best to analyse the data.

5. Methods of Analysis

5.1 Chapter Overview

This relatively long chapter describes the methods used here to measure fund performance, and is in five main parts.

Much of the analysis uses Generalised Auto-Regressive Conditional Heteroscedasticity (GARCH) models. A GARCH model consists of two equations estimated simultaneously: a mean equation and a variance equation.

The first main part: section 5.2 Mean Equations on p.61, describes the mean equation specifications relevant to fund performance measurement. It is only in a GARCH modelling context that these come to be called "mean equations" – they are simply the capital asset pricing model and market model that have dominated portfolio performance research for many years (and variations on these).

The second part: section 5.3 Heteroscedasticity, ARCH and its Detection on p.67 describes how straightforward ordinary least squares (OLS) estimation of these mean equations tends to produce unreliable results due to the presence of heteroscedasticity in financial market data such as that used here. More reliable results require either use of 'robust' OLS or explicit modelling of the heteroscedasticity. Heteroscedasticity in financial data is typically of a well-defined form – Auto-Regressive Conditional Heteroscedasticity (ARCH). Two methods for the detection of ARCH are presented.

The third main part: section 5.4 Variance Equations on p.73 describes the diversity of specifications that are available to model ARCH of different orders, with asymmetric effects, etc. An appropriate mean equation together with a suitable variance equation forms a GARCH model that can overcome the heteroscedasticity problem discussed in the previous section – and also provide useful information that 'robust' OLS does not.

The fourth main part: section 5.5 Sets of Candidate Models on p.78 considers the various ways in which these mean equations and variance equations might be combined into a diversity of GARCH models, defining sets of GARCH models that are relevant to particular purposes.

The fifth main part: section 5.6 Model Selection on p.82 then presents three simple criteria that are used to select from these sets of GARCH models the single GARCH model that best fits the data for a particular fund over a particular time period.

Section 5.7 on p.87 concludes this chapter.

The methods of analysis described in this chapter were implemented by means of batch programs run on Eviews 5.1 software. An example of such a batch program is provided in Appendix A on p.210.

5.2 Mean Equations

5.2.1 Importance of a Model of Equilibrium Portfolio Performance

Each investment fund under consideration here, whether 'ethical' or 'conventional' is a managed portfolio of company shares whose composition may be varied over time, so that the terms 'fund' and 'portfolio' are somewhat interchangeable in this context.

One can consider simple measures of portfolio performance such as the mean and standard deviation taking each fund in isolation. However, these are unsatisfactory measures of portfolio performance since the business of portfolio management is a matter of earning returns from bearing and managing the risk entailed in holding some subset of the equities available in the market.

From this it follows that portfolio performance measurement is only meaningful by making use of a model of equilibrium portfolio return in relation to market risk (Haugen, 2001). If the model used is correct, consistent observation of returns above the equilibrium level suggested by the model would imply that fund management has succeeded in 'beating the market' on a risk-adjusted basis. If the correctness of the model is in doubt, so too are any conclusions that may be drawn about portfolio performance.

5.2.2 The Capital Asset Pricing Model (CAPM) And Fund Performance

Previous academic research on UK and EU ethical fund performance, for example Kreander et al. (2005) and most of the previous research on which it draws (see section 2.4 on p.10), makes use mainly of risk-adjusted portfolio performance measures derived from the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965a,b) and Mossin (1966), applied to performance assessment by Treynor (1965) and Jensen (1969). This is also true of many studies of conventional unit trusts – for example Leger (1997) and Blake and Timmermann (1998) although often a CAPM-style model is modified by addition of other 'factors', for example the Carhart (1997) model used by Otten and Bams (2002).

The Sharpe-Lintner CAPM approach to portfolio performance assessment is typically based on estimation of the "ex post characteristic line" equation (or a further development of this):

$$r_{pt} - r_{ft} = \alpha_p + \beta_p \left(r_{mt} - r_{ft} \right) + \varepsilon_{pt} \qquad (1)$$

where r_{pt} is the return to the portfolio (or here, the investment fund) in period t and r_{ft} is the return to a risk-free asset so that r_{pt} - r_{ft} is the 'excess return' to the portfolio in period t (i.e. the return additional to that which is available 'risk free'). r_{mt} is the return to the 'market portfolio' and ε_{pt} is a random error term.

In empirical applications equation (1) is estimated by linear regression analysis. The return to the 'market portfolio' is typically represented by an appropriate stock market index such as the FTSE All share index listed as benchmark by FCE* and peers in Table 3-1 on p.30 above or the other benchmarks listed against the dozen ethical funds and peers in Table 4-3 to Table 4-14 on p.46. (It was apparent in section 2.4 on p.10 above that the appropriate choice of benchmark is not always clear-cut, particularly for ethical funds, and has been subject to debate. For example Luther and Matatko (1994) and Gregory et al. (1997) proposed inclusion of a second 'market' variable in addition to r_{mt} in order to account for the tendency of ethical funds to invest in smaller companies.)

Interpretation of the estimated coefficients (if accurate) in CAPM equation (1) above provides information about portfolio performance, as follows.

Estimated coefficient α_p, the intercept in CAPM equation (1), is 'Jensen's alpha' or simply 'alpha': a measure of risk-adjusted portfolio performance, since theory suggests that in equilibrium this will be zero. Non-zero 'alpha' α_p indicates 'abnormal' returns arising from selection of the chosen subset of market assets. Positive 'alpha' α_p implies that asset selection has succeeded in 'beating the market', whereas negative 'alpha' α_p indicates 'under-performance' relative to the market index, on a risk-adjusted basis.

The important caveat is that in sample data 'alpha' α_p estimates somewhat different from zero are to be expected by chance alone. Careful testing is needed to establish whether observed non-zero 'alpha' α_p estimates are statistically significant, i.e. unlikely to be due to chance alone, and hence informative regarding portfolio performance.

β_p, 'beta', is the portfolio's normalised covariance with market movements. 'Beta' β_p is a measure of the extent to which portfolio returns rise when the market index rises, and fall when the market index falls. In equilibrium a fund with 'beta' β_p somewhat less than 1 is expected to earn a mean return intermediate between the risk-free rate and the return to the market index.

A refinement of the CAPM that was introduced briefly in section 2.4.1 on p.10 is the incorporation not only of fund manager 'selection ability' as measured by 'alpha' α_p above but also of possible 'timing ability'. The timing of the purchase and sale of shares - so that a portfolio may have higher 'beta' β_p when the market is rising than when the market is falling - is another possible source of superior fund performance (Fama 1972). Also, importantly, as shown by Black, Fraser and Power (1992) and noted by Kreander et al. (2005), if fund managers <u>do</u> vary 'beta' β_p in this way, then empirical estimates of 'alpha' α_p in equation (1), which assumes that 'beta' β_p is constant over time, will be unreliable, possibly leading to incorrect conclusions regarding fund performance.

Thus timing ability is not only potentially important in its own right, it can also adversely affect measurement of selection ability ('alpha' α_p) if it is ignored when present.

One method of incorporating such market timing, previously applied to ethical investment performance research by Kreander (2002, 2005), follows Henriksson and Merton (1981):

$$r_{pt} - r_{ft} = \alpha_p + \beta_p\left(r_{mt} - r_{ft}\right) + b_1^T D_t^T\left(r_{mt} - r_{ft}\right) + \varepsilon_{pt} \qquad (2)$$

Equation (2) differs from (1) by inclusion of a term featuring D_t^T. D_t^T is a 'timing dummy' variable assigned a value of zero for all periods when $r_{mt} - r_{ft} < 0$ (i.e. the market index is falling) and a value of 1 when $r_{mt} - r_{ft} > 0$ (market index is rising). Thus in estimating equation (2), significant and positive b_1^T would be evidence of fund manager timing ability – increased exposure to market risk when the market is rising, and less exposure when the market is falling.

The literature provides a second simple method for detecting market timing that appears not previously to have been used in ethical fund research. Rather than the piecewise continuous line of Henriksson and Merton (1981), Treynor and Mazuy (1966) propose fitting a quadratic function:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + c_2(r_{mt} - r_{ft})^2 + \varepsilon_{pt} \qquad (3)$$

In equation (3) significant and positive c_2 would be evidence of timing ability. The Treynor and Mazuy (1966) approach was later refined by Bhattacharya and Pfleiderer (1983).

As there is no a priori reason to prefer either the Henriksson and Merton (1981) approach of equation (2) or the Treynor and Mazuy (1966) approach of equation (3) it may be that in empirical work any timing behaviour of a particular fund may be better modelled by one or other of these equations. Therefore in what follows both are used, and the model best describing the data is selected.

5.2.3 CAPM Problems And The Market Model

Although very widely used, the CAPM relies on a series of assumptions the appropriateness of which has been questioned, as follows.

Inclusion of variable r_{ft} in the equations above reflects the assumption underlying the Sharpe-Lintner CAPM that unlimited opportunities for both lending and borrowing are available at a common risk-free rate of interest. Clearly this situation applies only approximately in actual financial markets. In empirical work the return to one-month Treasury Bills or similar is generally used as a proxy (as here).

The term "market portfolio" (with returns r_{mt}) is on occasions used somewhat loosely but strictly speaking refers to "the portfolio of all invested wealth" (Campbell et al. 1997, p.182). While "invested wealth" can take various forms, in empirical work of this type the return to the market portfolio is typically approximated by the return to an appropriate broad stock market index such as (for UK securities) the FTSE All Share index. The inevitable difference between "all invested wealth" and what is captured by a stock market index has been referred to as 'the unobservability of the market portfolio' (Roll 1977).

As Campbell et al. (1997) make clear, the Sharpe-Lintner CAPM as typically implemented in equation (1) relies on further assumptions in addition to the unlimited availability of a common risk-free borrowing and lending rate and the comprehensiveness of the market portfolio:

> *...if investors have homogeneous expectations and optimally hold mean-variance efficient portfolios then, in the absence of market frictions, the portfolio of all invested wealth, or the market portfolio, will itself be a mean-variance efficient portfolio. The usual CAPM equation is a direct implication of the mean-variance efficiency of the market portfolio.*

Thus for the CAPM result to hold accurately assumes particular expectations about market movements and particular types of preferences on the part of individual investors, and also a lack of "market frictions". Eichberger and Harper (1997) provide an excellent treatment of the CAPM, including a derivation of equation (1) from first principles in which the underlying assumptions can be seen in operation.

The CAPM is an example of what Campbell et al. (1997) describe as 'economic models' which "restrict the parameters of statistical models to provide more constrained normal return models" (p.156). (Note that "normal" here is being used in the sense of "usual" or "equilibrium" and not the normal or Gaussian probability distribution.)

Empirical implementation of any portfolio performance model (including 'economic models' such as the CAPM) will rely on statistical assumptions. Thus in a sense all implemented models are 'statistical models'. The possible attraction of imposing further restrictive economic assumptions on such 'statistical models' (thereby producing an 'economic model') is "the potential opportunity to calculate more precise measures of the normal return" (ibid) – if the restrictions are valid.

There is an enormous and not entirely conclusive literature exploring the validity and empirical accuracy of the CAPM. Whilst noting that "...the CAPM remains a widely used tool in finance" (p.217), in discussing the choice of model for event studies Campbell et al. observe the following:

> *The Capital Asset Pricing Model was commonly used in event studies during the 1970s. During the last ten years, however, deviations from the CAPM have been discovered, and this casts doubt on the validity of the restrictions imposed by the CAPM on the market model. Since these restrictions can be relaxed at little cost by using the market model, the use of the CAPM in event studies has almost ceased. (p.156)*

The market model is, in Campbell et al.'s terminology, a 'statistical model' and involves estimation of a simple linear relation between the return of the asset under consideration and that of the market portfolio:

<u>Market Model</u>

$$r_{pt} = \alpha_p + \beta_p r_{mt} + \varepsilon_{pt} \qquad (4)$$

Comparing equation (1) on page 62 with (4) the "little cost" in implementing the market model as opposed to the CAPM is evident: the linear relationship is the same in both cases, but one (the CAPM) considers excess returns, after subtraction of 'risk-free rate' r_{ft}, while the other (market model) considers investment returns without making this adjustment.

Given the above, both the CAPM and the market model are considered in what follows.

5.2.4 Time-Varying Alpha and Beta: Event Dummy Variables

As described above in section 3.2 on p.26 one ethical fund, FCE*, was launched as a 'conventional' non-ethical unit trust and later adopted ethical investment objectives in March-96. There was also a change in fund management in Sept-97. Similarly to the manner in which Henriksson and Merton (1981) use a 'timing' dummy variable to distinguish between time periods when the market is rising and when it is falling, an 'ethical' dummy variable can be used to distinguish between periods before and after such events. The two approaches can also be combined as follows:

$$r_{pt} = \mathrm{a}_1 + \mathrm{a}_1^E D_t^E + \mathrm{b}_1 r_{mt} + \mathrm{b}_1^E D_t^E r_{mt} + \mathrm{b}_1^T D_t^T r_{mt} + \varepsilon_{pt} \qquad (5)$$

Equation (5) applies the Henriksson and Merton (1981) 'timing' dummy D_t^T to the market model with the additional use of 'ethical' dummy D_t^E to provide estimates of pre- and post-ethical 'alpha' and 'beta'. Prior to the adoption of ethical investment principles $D_t^E = 0$ so that pre-ethical 'alpha' is estimated by coefficient a_1. After the change

$D_t^E = 1$ so that post-ethical 'alpha' is given by $(a_1 + a_1^E)$. Whether or not 'alpha' is in fact influenced by the change in investment principles therefore depends on the magnitude and statistical significance of a_1^E. Similarly, pre-ethical 'beta' is b_1 and post-ethical 'beta' is $(b_1 + b_1^E)$, if b_1^E is statistically significantly different from zero. The duration of any post-ethical effect can be varied by having D_t^E return to zero after a number of months. (Note that equation (5) is based on the market model of equation (4); this method of measuring timing ability can equally be applied to the CAPM of equation (1).)

Equation (6) is entirely similar, except that the Treynor and Mazuy (1966) market timing method is used.

$$r_{pt} = \mathrm{a}_2 + \mathrm{a}_2^E D_t^E + \mathrm{b}_2 r_{mt} + \mathrm{b}_2^E D_t^E r_{mt} + c_2 r_{mt}^2 + \varepsilon_{pt} \qquad (6)$$

Both of these approaches are used in what follows.

In addition to the switch from non-ethical to ethical investment in March-96, Fund FCE* also underwent a change in management at a different date, Sept-97. The possible influence of the management change can be modelled in an entirely similar way using a dummy variable, say, D_t^M rather than D_t^E, with the dates on which this is zero or one adjusted accordingly An indication of which change (in investment approach or in management) was most significant in determining financial performance can then be gained by examining which dummy variable specification, if any, best fits the data.

5.3 Heteroscedasticity, ARCH and its Detection

5.3.1 The Effect of Heteroscedasticity

Nothing has so far been said about how linear equations (1) to (6) in the previous section might be estimated, except that some form of regression analysis is typically employed. The usual starting point is 'ordinary' least-squares regression or 'OLS' in which the sum of the squared differences between the data and the 'best-fit' regression line is minimised. In addition to being easily implemented, OLS estimation has attractive properties according to the Gauss-Markov theorem which states:

> *Given the assumptions of the classical linear regression model, the least-squares estimators, in the class of unbiased linear estimators, have minimum variance... (Gujarati 1995, p.73).*

That is, if the relevant conditions hold, OLS estimates of our CAPM or market model coefficients will be:

- unbiased: i.e. the expected value of the OLS coefficient estimate is equal to the true value
- efficient: i.e. have minimum variance amongst the class of linear unbiased estimators.

Amongst 'the relevant conditions' of the classical linear regression model is the condition of 'equal variance' or homoscedasticity:

$$E(\varepsilon_{pt}^2) = \sigma^2 \qquad \forall t \tag{7}$$

Equation (7) stipulates that the expected value of the square of the residuals from equations (1) to (6) should at all times be equal to some value σ^2 i.e. should be constant over time.

Simply put, OLS residuals are assumed to have constant variance. If, in a given instance, they do not – i.e. if there is heteroscedasticity, the desirable properties of OLS estimation will not fully apply, potentially leading, in this case, to erroneous conclusions regarding portfolio performance.

All econometrics textbooks discuss this issue. If heteroscedasticity is present, OLS estimates are still unbiased, but they are no longer efficient. This has the consequence that "Conventional OLS coefficient standard errors are incorrect, and the conventional test statistics based on them are invalid" (Johnston and DiNardo 1997 p.162) although the coefficient estimates themselves are unaffected.

As an illustration, Figure 5-1 shows OLS residuals from estimation of the simple market model in equation (4) on p.66, for fund MCI (one of FCE*'s peers). Visual inspection suffices to establish that heteroscedasticity is present –the residuals are much more variable in some periods than in others with a 'quiet period' from around 1994 to 1998.

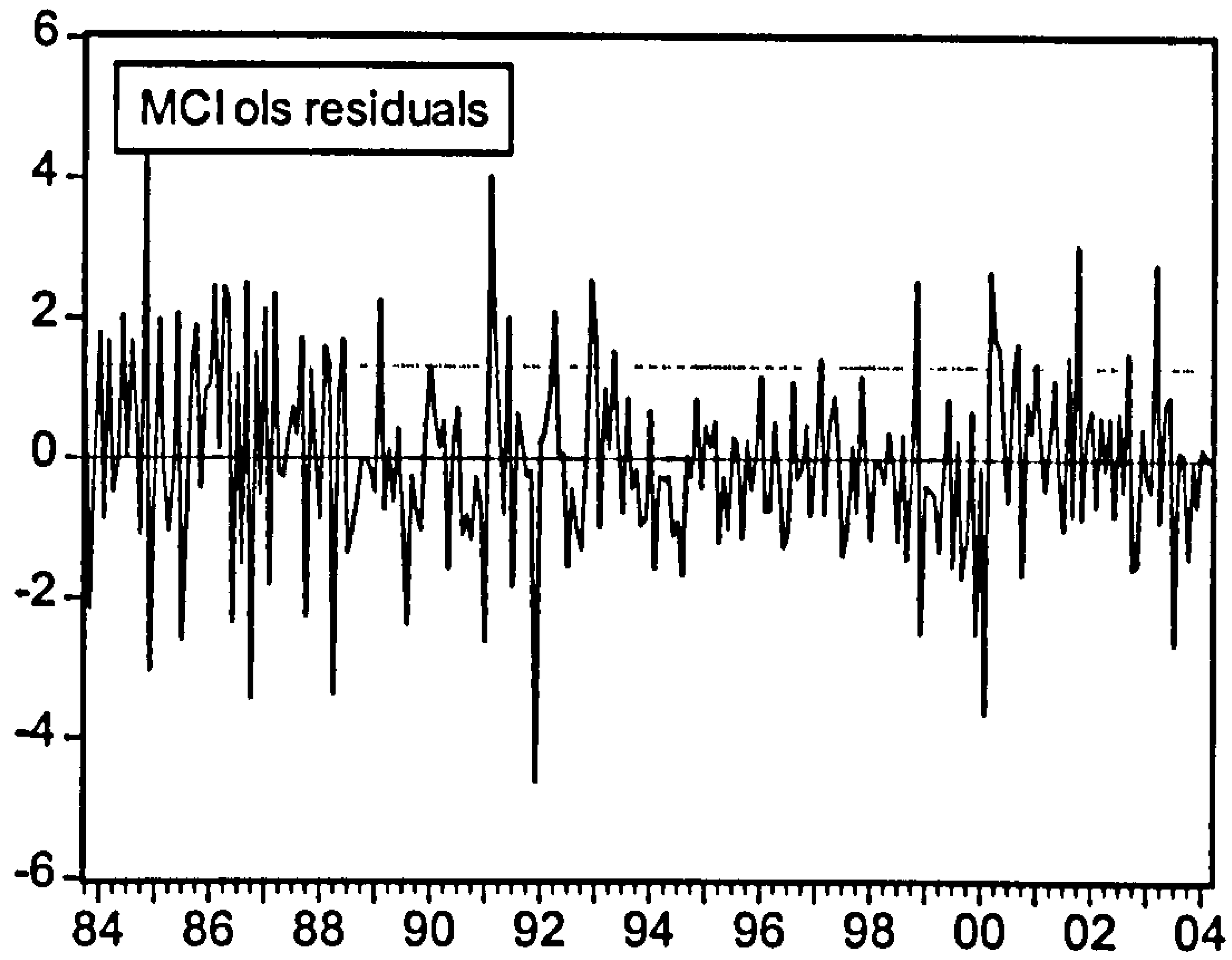

Figure 5-1 Example OLS residuals from market model estimation, fund MCI

Detection of heteroscedasticity does not, of course, rely on visual inspection. For example, White (1980) provides a general statistical test of the null hypothesis of no heteroscedasticity in residuals from least squares regressions. In the MCI example here White's test firmly rejects the null hypothesis of no heteroscedasticity with a p-value of 0.008 well below the conventional 5% significance level i.e. the test strongly supports the visual impression that heteroscedasticity is present. It becomes clear below that all the financial data considered here has this property i.e. is heteroscedastic. (Since White's (1980) test is applicable only where a model has been estimated using OLS estimation and where detection of general heteroscedasticity of unknown form is the aim – neither of which turns out to be relevant to what follows – White's test is not presented in detail here; other techniques are presented in more detail below.)

Once it is established that heteroscedasticity is present and therefore the usual t-tests etc. on coefficient estimates are invalid, two broad options are available.

Option One: Robust OLS Estimation

The first option is to persist with OLS coefficient estimation, supplemented by use of an alternative method to calculate 'robust' standard errors and t-statistics that are valid in the presence of heteroscedasticity of unknown form.

In addition to the test for detection of heteroscedasticity White (1980) provided a method for the calculation of such 'heteroscedasticity-consistent' standard errors and t-statistics. Subsequently Newey and West (1987) provided a more general method for 'heteroscedasticity-and-autocorrelation-consistent' (HAC) standard errors and t-statistics.

This first option – OLS plus HAC standard errors – is employed by Kreander et al. (2005 p.1483) although this is not discussed in detail, being mentioned in a footnote to their Table 4a.

Option Two: Explicit Heteroscedasticity Modelling

A second option is to explicitly model the heteroscedasticity as part of the estimation process. While potentially laborious, this seems preferable for three reasons.

Firstly, if the existing heteroscedasticity is correctly modelled, as opposed to making an allowance for general 'unknown' heteroscedasticity, the results obtained seem likely to be more accurate and more reliable.

Secondly, in financial data of the type employed here, the heteroscedasticity expected is not of "unknown form" but of a particular type that is amenable to modelling. This is 'volatility clustering', whereby "large returns (of either sign)... follow large returns, and small returns (of either sign)... follow small returns" (Brooks, 2002). Such volatility clustering is evident in the OLS residuals in Figure 5-1 on page 69 above. Volatility clustering can be described by Auto-Regressive Conditional Heteroscedasticity or ARCH models, for which well-established techniques are available.

Thirdly, the results of such heteroscedasticity modelling yield useful information about the volatility of fund performance over time that is not provided by 'robust' OLS.

This second - explicit heteroscedasticity modelling - option is adopted in what follows.

5.3.2 ARCH Detection: Q-Statistics for Squared Residuals

Enders (2004, p.119) describes two methods for the detection of ARCH, making use either of the autocorrelations between lagged squared residuals (section 5.3.2, here) or of an auxiliary regression using lagged squared residuals (section 5.3.3 on p.71).

Volatility clustering implies that the magnitude (but not the direction) of regression residuals at a point in time is related to the magnitude of recent preceding residuals. An intuitive way to check for this is to square the residuals and look for such correlations between adjacent (in this case monthly) values. Autocorrelation τ_k measures the correlation between values of the squared residuals a given number of lags apart:

$$\tau_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} \qquad (8)$$

where in this case y_t is the square of the OLS residual at time t.

The Q-statistic of Ljung and Box (1978) provides a useful test of the null hypothesis of no autocorrelation up to order k:

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{\tau_j^2}{T-j} \sim \chi^2(k) \qquad (9)$$

5.3.3 ARCH Detection: The ARCH-LM Test

An alternative approach to testing for volatility clustering is the Lagrange Multiplier (LM) test of Engle (1982) which again looks at squared residuals this time running an auxiliary regression of the squared residuals on up to q lags:

$$\varepsilon_t^2 = \lambda_0 + \sum_{s=1}^{q}\lambda_s \varepsilon_{t-s}^2 + \upsilon_t \qquad (10)$$

This regression of (squared) residuals on (lags of) themselves in equation (10) accords well with the technical name given to 'volatility clustering' of this type: Auto-Regressive Conditional Heteroscedasticity, or ARCH.

The product of the number of observations and the coefficient of determination (R^2) from this auxiliary equation – known as 'obs-R-squared' provides a test of the null hypothesis of no ARCH up to order *q* as 'obs-R-squared' is asymptotically distributed as $\chi^2(q)$.

5.3.4 ARCH Detection Example

Table 5-1 shows the result of ARCH tests on residuals from the ordinary least squares estimation of the basic market model in equation (4) on p.66 for ethical fund FCE* and its four peers (see Table 3-1 on p.30).

Recall that both the Q-statistic and LM methods test the null hypothesis of no ARCH up to a given order (depending on the number of lags used in calculating the test statistic). Thus a p-value < 0.05 implies rejection of this null hypothesis at the conventional 5% significance level.

Table 5-1 shows the resulting p-values when testing for ARCH of order up to 8, with instances where $p < 0.05$ (i.e. ARCH is present) highlighted by shading. In every case the null hypothesis is rejected for one or more lag lengths.

Table 5-1 Testing for ARCH in FCE* and peers: p-values from Q-statistic and LM tests

	FCE*		SUG		IUG		MCI		AAE	
lags	Q-stat	LM	Q-stat	LM	Q-stat	LM	Q-stat	LM	Q-stat	LM
1	0.000	0.000	0.022	0.023	0.359	0.358	0.02	0.021	0.008	0.008
2	0.000	0.000	0.069	0.078	0.012	0.014	0.067	0.064	0.028	0.023
3	0.000	0.000	0.061	0.076	0.000	0.000	0.144	0.127	0.044	0.046
4	0.000	0.000	0.072	0.119	0.000	0.000	0.194	0.171	0.086	0.094
5	0.000	0.000	0.021	0.043	0.000	0.001	0.083	0.100	0.000	0.000
6	0.000	0.000	0.002	0.015	0.000	0.002	0.125	0.160	0.000	0.000
7	0.000	0.000	0.000	0.005	0.000	0.000	0.183	0.220	0.000	0.000
8	0.000	0.000	0.000	0.004	0.000	0.000	0.255	0.316	0.000	0.000

OLS residuals for fund MCI were shown above in Figure 5-1 on page 69, to illustrate what ARCH 'looks like', and the results in Table 5-1 confirm this visual impression.

Having established that ARCH is present, and having decided to model this rather than to adopt the Newey and West (1987) robust estimation approach, the question is then – which ARCH specification to use? A considerable variety are available, as described in the next section.

5.4 Variance Equations

5.4.1 GARCH(1,1)

The most commonly applied model of the ARCH type is the GARCH(1,1) (Generalised ARCH) model of Bollerslev (1986) and Taylor (1986).

In implementing a model of the GARCH type both an equation describing the mean level of returns (e.g. any of equations (1) to (6) on pages 62 to 67 or similar, as appropriate), and an equation describing the variance of returns about this line are simultaneously estimated, typically by the method of maximum likelihood (i.e. not by ordinary least squares).

The GARCH(1,1) variance equation specification is:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2 \tag{11}$$

In equation (11) σ_t^2 is conditional variance: an estimate of variance about the mean equation at time t based on information up to time t, and ε_t^2 is the (squared) residual from the mean equation at time t. Thus conditional variance at time t, σ_t^2, is estimated as dependent upon its own value one time-period prior to time t, σ_{t-1}^2 and also dependent upon the value of the mean-equation residual one period prior to time t, ε_{t-1}^2 (i.e. one lag of each). Lagged mean-equation residual ε_{t-1}^2 provides 'news' about volatility from the previous period, as by definition a residual is a measure of the difference between the mean equation expectation and what actually happens in the data.

Thus implementing equation (11) in a GARCH(1,1) model involves simultaneous empirical estimation of coefficients in two equations: mean equation coefficients from any of equations (1) to (6) or similar, as appropriate, plus estimation of variance equation coefficients γ_0, γ_1 and δ_1, using the method of maximum likelihood.

Often the GARCH(1,1) specification is treated as 'one-size-fits-all': "in general a GARCH(1,1)... will be sufficient to capture the volatility clustering in the data" (Brooks 2002), and this is by far the most commonly used specification.

5.4.2 GARCH(p,q)

More generally one can have a GARCH(p,q) specification:

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j \sigma_{t-j}^2 \qquad (12)$$

The GARCH(p,q) specification in equation (12) includes p lags of squared mean-equation residuals ε_t^2 and q lags of conditional variance σ_t^2. In the (rather unhelpful) terminology commonly used:

- lags of squared mean-equation residual ε_t^2 are called ARCH terms (p of these) and
- lags of conditional variance σ_t^2 are called GARCH terms (q of these).

(Note, the above follows Alexander (2001, p.72) in that in the GARCH(p,q) notation the first number, p, denotes number of lags of squared residuals and the second number, q, denotes number of lags of conditional variance. This agrees with other authors such as Cuthbertson (1996, p.440) and Johnston and DiNardo (1997, p.197). However, confusingly, this is not a universal practice. Some authors do the reverse, listing the number of lags of conditional variance first, followed by the number of lags of squared residuals. Such authors include Brooks (2002, p.454), Campbell et al. (1997, p.483), Enders (2004, p.118), Hamilton (1994, p.665) and Patterson (2000, p.713). In what follows the Alexander (2001) convention is followed consistently.)

Although the GARCH(p,q) model – indeed the GARCH(1,1) – is by far the most commonly used, a considerable number of variants have been proposed, each incorporating a further refinement. For completeness, the analysis that follows investigates every GARCH variant model that is supported by Eviews 5.1 software, selecting the 'best' fit to the data in each particular case. These models are now briefly described. Fuller discussion is available in many textbooks, for example Alexander (2001), Campbell et al. (1997), Enders (2004) and Patterson (2000).

5.4.3 GARCH With Additional Regressors

It is possible to include other regressor variables in the conditional variance equation. For example, Enders (2004, p.141) gives an example using a dummy variable to determine whether the New York terrorist attacks of 11 September 2001 increased the volatility of asset returns. Adopting this technique, an 'ethical' dummy variable proves useful in what follows:

$$\sigma_t^2 = \gamma_0 + \gamma_E D_t^E + \gamma_1 \varepsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2 \qquad (13)$$

Equation (13) shows the GARCH(1,1) specification of equation (11) with the addition of 'ethical' dummy variable D_t^E. Where, as for fund FCE*, a fund is implementing ethical investment principles only after a particular date, coefficient γ_E in equation (13) estimates the magnitude and statistical significance of any resulting change in variance about the benchmark. This provides a useful complement to the similar use of dummy variables to detect possible changes in mean-equation 'alpha' α_p or β_p, 'beta', described in section 5.2.4 on p.66.

Such a variance regressor can also be introduced into the many variant GARCH specifications described below.

5.4.4 Threshold GARCH, or TARCH

Equation (14) shows the Threshold GARCH or TARCH specification introduced by Zakoian (1994) and Glosten et al. (1993):

$$\sigma_t^2 = \gamma_0 + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \eta_k \varepsilon_{t-k}^2 I_{t-k} \qquad (14)$$

where 'news' dummy variable $I_{t-k} = 1$ if $\varepsilon_t < 0$ and is zero otherwise.

The TARCH specification incorporates the notion that a positive residual ε_t in the mean equation (for example, in the basic market model equation (4) on p.66) indicates that in that period actual portfolio performance was greater than expected – which is 'good news'. Conversely $\varepsilon_t < 0$ is 'bad news' – in that period the portfolio underperformed relative to the mean equation expectation.

Dummy variable I_{t-k} allows for the impact of such 'news' to be asymmetric, as bad news may be expected to increase volatility more then good news. This asymmetry is known as the 'leverage' effect. In equation (14) the impact on σ_t^2 of 'good news' (positive mean-equation residuals) is γ_j while that of negative residuals is $\gamma_j + \eta_k$, with the expectation that $\eta_k > 0$.

Note that a TARCH specification involves selecting not only *p* (the number of lags of mean-equation residuals) and *q* (the number of lags of conditional variance) but also *r*: the 'threshold order'.

5.4.5 Exponential GARCH, or EGARCH

Other GARCH variant specifications incorporate such asymmetry or 'leverage' in different ways, for example the Exponential GARCH or EGARCH model of Nelson (1991).

$$\log(\sigma_t^2) = \gamma_0 + \sum_{i=1}^{p} \gamma_j \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{q} \delta_i \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \eta_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{15}$$

In EGARCH equation (15) the impact of 'news' from mean-equation residuals is asymmetric if η_k is significantly different from zero, and there is 'leverage' such that 'bad news' has a greater impact on volatility than 'good news' if $\eta_k < 0$.

Whereas in the TARCH specification this leverage effect is quadratic, in the EGARCH specification it is exponential (i.e. the impact of larger residuals is greater); also the EGARCH specification ensures non-negative conditional variance (a reasonable requirement) whereas the TARCH is not constrained to avoid delivering meaningless negative values.

Again, an EGARCH specification entails selection of values for *p*, *q* and *r*; in this context the value of *r* is called the 'asymmetry order'.

5.4.6 Power ARCH, or PARCH

A further GARCH variant incorporating asymmetry amongst other features is the Power ARCH or PARCH specification of Ding et al (1993) based on work by Taylor (1986) and Schwert (1989):

$$\sigma_t^{\lambda} = \gamma_0 + \sum_{i=1}^{p} \gamma_i \left(|\varepsilon_{t-i}| - \eta_i \varepsilon_{t-i} \right)^{\lambda} + \sum_{j=1}^{q} \delta_j \sigma_{t-j}^{\lambda} \tag{16}$$

where $\lambda > 0$, $|\gamma_i| \leq 1$ for $i = 1, \ldots, r$, $\gamma_i = 0$ for all $i > r$, and $r \leq p$.

Note that the left hand side of PARCH equation (16) is not conditional variance σ_t^2, but conditional standard deviation σ_t raised to some power λ. Asymmetry is again indicated by significant and non-zero η_k if optional η_k parameters are included up to order r where $r \leq p$.

A PARCH specification entails selection of values for p, q, r and λ, but Eviews 5.1 provides an option to estimate, rather then to impose, λ.

5.4.7 Component GARCH, or CGARCH

The component GARCH, or CGARCH specification of Engle and Lee (1993a, 1993b) and Engle and Mezrich (1995) is not concerned with asymmetry as the variants considered so far have been (although asymmetric impacts can be incorporated into the CGARCH model, for example by incorporating a TARCH term). Rather the CGARCH specification decomposes conditional variance into 'permanent' and 'transitory' components.

The long-run steady state variance of the GARCH(1,1) model in equation (11) on page 73 can be obtained by setting $\sigma_t^2 = \sigma^2$, i.e. equal to some constant value and then solving for σ^2, giving:

$$\sigma^2 = \frac{\gamma_0}{1-\gamma_1-\delta_1} \tag{17}$$

Using this result GARCH(1,1) equation (11) can be re-written as:

$$\sigma_t^2 = \sigma^2 + \gamma_1\left(\varepsilon_{t-1}^2 - \sigma^2\right) + \delta_1\left(\sigma_{t-1}^2 - \sigma^2\right) \tag{18}$$

Equation (18) illustrates the fact that the usual GARCH(1,1) specification incorporates assumed mean-reversion around a steady state value of σ^2 that is assumed to remain constant over time i.e. movement away from the constant steady state mean is transitory. The CGARCH specification replaces constant σ^2 with a time-varying 'permanent' component:

$$m_t = \gamma_0 + \rho(m_{t-1} - \gamma_0) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (19)$$

5.4.8 GARCH-in-Mean, or GARCH-M

The GARCH-M specification was first proposed by Engle et al. (1987). It combines one of the various GARCH specifications discussed above together with a mean equation in which conditional variance now appears as an explanatory variable. For example, a GARCH-M(1,1) model might estimate the usual GARCH(1,1) specification in equation (11) above on page 73 together with a simple market model mean equation such as equation (4) on page 66. However, the market model in equation (4) would be amended to also include the GARCH(1,1) estimated conditional variance as a dependent variable:

$$r_{pt} = \alpha_p + \beta_p r_{mt} + \theta_p \sigma_t^2 + \varepsilon_{pt} \quad (20)$$

In equation (20) coefficient θ_p captures any impact of increasing volatility on mean return to a portfolio. The GARCH-M specification is of importance in some financial applications where the expected return on an asset is related to the risk or volatility of the asset.

5.5 Sets of Candidate Models

This section reflects on the implications for data analysis of the variety of mean equation and variance equation specifications that are available, and arrives at reasonable sets of GARCH models for consideration in the different circumstances that apply in the present research.

The relatively brief discussion in this section is supplemented by more extensive discussion and listings of sets of candidate models in Appendix A: Key To Model Sets on p.210.

Considering the GARCH(p,q) specification in equation (12) on p.74, one might reasonably wish to consider values of p (number of lags of mean-equation residual ε_t^2 - ARCH terms) and q (lags of conditional variance σ_t^2 - GARCH terms) up to the second order i.e. up to p = 2 and q = 2 i.e.:

GARCH(1,0) sometimes written as ARCH(1)
GARCH(1,1)
GARCH(2,1)
GARCH(1,2)
GARCH(2,2)

Taking each of these together with a particular mean equation specification such as equation (4) on page 66 gives 5 GARCH models of the symmetric GARCH(p,q) type.

Similarly, with p and q up to order 2, the TARCH specification in equation (14) on p.75 provides 5 models with threshold order $r = 1$ and a further 5 models with $r = 2$. And likewise the EGARCH specification of equation (15) also yields a further 10 models with asymmetry order up to 2, while the PARCH specification of equation (16) with threshold order $r = 1$ yields a further 5 models. Rather than 5 more models, PARCH with threshold order $r = 2$ yields only two more models due to the restrictions imposed upon the parameters. This gives a total of 32 GARCH models.

Furthermore, each of these 32 models can be estimated with or without the ARCH-in-mean component of equation (20) on p.78, giving 64 models. To this list can be added the component, or CGARCH specification described in equations (18) and (19) on page 77, plus its asymmetric version (incorporating a TARCH term) bringing the total number of GARCH variant specifications that might be paired with any one particular mean equation specification to 66. To this list should be added the ordinary least squares (OLS) model (i.e. a mean equation with no variance equation), to check that (as expected) heteroscedasticity is indeed a problem – bringing the number of models for this single mean equation to 67.

As described in section 5.2 on p.61, there are a number of mean equation specifications of interest besides the basic market model of equation (4) on p.66 in order to detect possible timing ability or changes in 'alpha' α_p or 'beta' β_p following a change in investment objectives. Similar comments regarding the 67 GARCH variant models apply equally to all such mean equation specifications.

The scale of the resulting data analysis exercise depends on the number of mean-equation specifications that are of relevance in a particular context. Where the number of relevant mean-equation specifications is few, the full range of variance equations can be fully explored relatively easily. Where the number of relevant mean-equation models is larger, it may be preferable (or necessary) to restrict the number of variance equations considered, perhaps using the 'one-size-fits-all' GARCH(1,1) model. The relevant information is summarised in Table 5-2 on p.80.

The columns to the right of Table 5-2 on p.80 headed M1, M2, etc., describe sets of GARCH models that might be estimated. In Table 5-2 the total number of models to estimate is the product of the three section totals for sections A, B and C.

Table 5-2 Model Sets

Model type	**No. of models**	**M1**	**M2**	**M3**	**M4**	**M5**
A: Market Timing						
Dummy, quadratic, none	3	•	•	•	•	•
Section total		3	3	3	3	3
B: Event Dummy Variables						
None	1	•	•	•	•	•
Ethical	7		•	•	•	
Management	7		•	•		•
Section total		1	15	15	8	8
C: Conditional Variance						
OLS (none)	1	•	•			
GARCH(1,1) only	1			•	•	•
All variants	66	•	•			
Section total		67	67	1	1	1
Total number of models		201	3015	45	24	24

Where the mean equation parameters can be regarded as unchanging over time (i.e. there is no switch of investment objectives as in the case of fund FCE*) the relevant mean equation is the simple market model of equation (4) on p.66 with the possible addition of allowance for market timing using either the piecewise continuous line of Henriksson and Merton (1981) in equation (2) on p.63 or the alternative quadratic method of Treynor and Mazuy (1966) in equation (3). Thus accounting for the possibility of market timing implies estimation of three mean equations for any given variance equation, and this is shown in the upper part of Table 5-2, "A: Market Timing". In Table 5-2 all model sets M1, M2, M3, M4 and M5 have a 'dot' marker against section

A: market timing, indicating that the possibility of market timing is always considered in the analysis that follows.

If, as in model set M1, market timing is allowed for (section A) but no event dummy variables are used (section B) and all 66 variance equation specifications plus the basic ordinary least squares model are used (Section C) this entails estimating a total of (3 x 1 x 67) = 201 models. This set M1 of 201 possible models is applicable to the dozen ethical funds and their peers described in chapter 4 Data II: Twelve Ethical Funds from p.34 onwards and whose results are presented in chapter 7 Analysis II: Twelve Ethical Funds from p.108 onwards.

However, in the analysis of fund FCE* and peers there is the additional consideration of the use of event dummy variables to detect any change in mean-equation intercept ('alpha' α_p) or slope ('beta' β_p) as described in section 5.2.4 on p.66 or in conditional variance (γ_E in equation (13) on p.75) that may occur due to either the switch to ethical investment objectives in March-96 or the fund management change in Sept-97.

There are seven ways of incorporating an event dummy variable as a mean-equation intercept dummy and/or a mean-equation slope dummy and/or a variance regressor: individually, in pairs, or all three at once. This is equivalent to selectively specifying parameters a_1^E or b_1^E in equations (5) and (6) on pages 66 and parameter γ_E in equation (13) on p.75 to be equal to zero. This is true both for an ethical event dummy variable and a management event dummy variable, as shown in section B of Table 5-2.

Table 5-2 shows that if, as in model set M2, all possible event dummy specifications are each combined with all possible variance equations, the total number of models to estimate and from which to select 'the best' is (3 x 15 x 67) = 3015. The question arises – how far is it reasonable to go in pursuit of comprehensiveness of approach?

In practice, the Eviews 5.1 software made this decision a pragmatic and simple one. The software and the batch program written for the purpose worked well when presented with 201 possible models. But when the same batch program was extended to allow for 3015 possible models, Eviews crashed at every attempt without providing any of the usual helpful error messages and would not run despite attempts to modify the batch program.

Therefore, in chapter 6, Analysis I: Family Charities Ethical (FCE*) the main analysis initially uses model set M3 shown in Table 5-2 combining the 'one-size-fits-all' GARCH(1,1) specification with market timing and event dummies entailing estimation of (3 x 15 x 1) = 45 models, and selection from these.

In order to discover the duration of each event dummy variable, it is also necessary to separately consider only the ethical event and then only the management change event, shown in Table 5-2 as model sets M4 and M5 each with 24 models.

In chapter 7, Analysis II: Twelve Ethical Funds, all 66 variance equation specifications (plus OLS) are used in combination with the 3 mean equation timing models and all event dummy specifications, giving the 201 models of model set M1.

5.6 Model Selection

Having estimated a set of candidate GARCH models as described in the previous section – which best fits the data? Three selection criteria are used.

For a given set of data, the 'best' model satisfies three criteria:

1. no residual ARCH
2. no redundant variables
3. minimum Akaike (1974) and/or Schwarz (1978) information criterion

Each of these criteria is explained in turn in the sections that follow.

5.6.1 The 'No Residual ARCH' Criterion

As described in section 5.3 on p.67, the use of GARCH models is driven by the problematic presence of heteroscedasticity of a particular form (ARCH) in the residuals of the mean equation. If a particular GARCH model (consisting of a particular mean equation specification and a particular variance equation specification) successfully captures the ARCH, then this model will have no ARCH in its residuals.

This first model selection criterion uses both of the ARCH detection methods described in sections 5.3.2 on p.70 and 5.3.3 on p.71. Models that do not pass both tests up to order 8 are rejected.

In addition to being intuitively reasonable, this model selection criterion is supported by Alexander (2001, p.97) : "if there is no autocorrelation in the squared standardised returns the GARCH model is well specified". This is equivalent to testing for autocorrelation of squared residuals as is done using the Q-statistic method in 5.3.2 on p.70.

However, this 'no residual ARCH' criterion in itself will select more than one 'good' model, so that further joint selection criteria are required.

5.6.2 The 'No Redundant Variables' Criterion

Elaborations upon the basic market model of equation (4) on p.66 and upon the GARCH(1,1) model of equation (11) on p.73 involve the estimation of additional 'optional' parameters in both the mean and variance equations such as, for example, quadratic timing coefficient c_2 in equation (6) in section 5.2.4 on p.66, or asymmetric leverage coefficient η_k in equation (14) on p.75 in section 5.4.4, etc.

A reasonable minimal model selection criterion is that such optional parameters should only be included in a model if they are statistically significantly different from zero at the conventional 5% level. Model specifications including optional parameters that prove not to be statistically significantly different from zero are rejected.

However, there is a slight complication when assessing the statistical significance of coefficients in GARCH models estimated by the method of maximum likelihood. As noted by Campbell et al. (1997, p.488):

> *The GARCH models we have considered imply that the distribution of returns, conditional on the past history of returns, is normal. Equivalently, the standardized residuals of these models... should be normal. Unfortunately, in practice there is excess kurtosis in the standardised residuals of GARCH models, albeit less than in the raw returns...*

This is a somewhat analogous problem to that encountered when considering the use of OLS estimation in the presence of heteroscedasticity above in section 5.3 on p.67 – only here we are dealing with maximum likelihood estimation in the presence of standardised residuals that are not normally distributed. If the relevant condition is not met then the estimated standard errors and p-values - on which judgements are usually made regarding the statistical significance of particular coefficients - are unreliable. Somewhat similarly to the OLS/heteroscedasticity case, Campbell et al. (1997) note that more than one course of action is available, in this case three broad options.

One possibility is to persist with maximum likelihood estimation but to model any excess kurtosis ('fat tails' relative to the normal distribution) using a Student-t distribution or Generalised Error Distribution.

A second possibility is not to use maximum likelihood estimation but instead to use an estimation method not reliant on the normality assumption such as the General Method of Moments.

A third option is to persist with maximum likelihood estimation without explicitly modelling any excess kurtosis. An estimator for standard errors and p-values that is 'robust' to deviation from the normality assumption was provided by Bollerslev and Wooldridge (1992) and is available with the Eviews 5.1 software used in the present research as a 'Heteroscedasticity Consistent Covariance' (HCC) option. <u>This third, HCC option, is used in what follows</u>, although it is acknowledged that it would also be of interest to compare results using the other options. Such application of maximum likelihood estimation in circumstances where the normality assumption is not known to be satisfied is called Quasi-Maximum Likelihood (QML) estimation.

In practice this means that both the usual maximum likelihood and the Bollerslev and Wooldridge (1992) HCC standard errors, z-statistics and p-values are estimated for each coefficient. In assessing the statistical significance of regression coefficients the standardised residuals are first tested for normality using the Jarque-Bera statistic (Bera and Jarque, 1980):

$$JB = \frac{T-k}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \sim \chi^2(2) \qquad (21)$$

where T is the number of observations, k is the number of estimated coefficients used to generate the series of standardised residuals, S is skewness and K is kurtosis.

If the null hypothesis of normality is rejected reference is made to the Bollerslev and Wooldridge (1992) HCC standard errors and p-values otherwise the usual maximum likelihood standard errors and p-values are used.

In this way models with 'redundant' parameters not statistically significant at the usual 5% level are identified and rejected, in a reliable way.

Together the previous 'no residual ARCH' criterion and this 'no redundant variables' criterion reject a large number of model specifications that are clearly unsuitable, but generally more than one model specification will pass both of these two tests. From these 'reasonable' models, some means is required of selecting 'the best'.

5.6.3 The 'Minimum Information Criterion' Criterion

In discussing the variety of time-series models available, Enders (2004) is worth quoting at length:

> *One natural question to ask of any estimated model is: How well does it fit the data? Adding additional lags for p and/or q will necessarily reduce the sum of squares of the estimated residuals. However, adding such lags entails the estimation of additional coefficients and an associated loss of degrees of freedom... there exist model selection criteria that trade off a reduction on the sum of squares of the residuals for a more parsimonious model. The two most commonly used model selection criteria are the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC)... ideally, the AIC and SBC will be as small as possible...* (p.69)

AIC and SBC are due to Schwarz (1978) and Akaike (1974) and can be calculated as:

$$AIC = T \log RSS + 2k \qquad (22)$$

$$SBC = T \log RSS + k \log T \qquad (23)$$

where

T is the number of observations

k is the number of parameters estimated in the model, and

RSS is the sum of the squared residuals (or 'residual sum of squares').

These information criteria are reported and calculated in a number of slightly different ways, but "all will select the same model" (Enders 2004).

Enders stresses the importance of making comparisons only between models for which the number of observations T is the same (which is always the case in the analysis that follows).

For given T it is evident that equations (22) and (23) consist of two terms. The first term in *RSS* (sum of squared residuals) will always decrease whenever an additional explanatory variable is added to a regression tending to lower AIC and SBC and thus lead to the selection of models with large numbers of regressors. The second term in k (number of estimated parameters) of course increases as additional regressors are added, tending to cause the model to be rejected in favour of another with fewer parameters. This is the "trade off" referred to by Enders above: if the additional regressors have no explanatory power, they will increase k with very little decrease in *RSS*, and so fail to reduce AIC or SBC.

Thus AIC and SBC provide a guide to parsimony in model selection – including enough regressors to provide a 'good fit' to the data, but not 'too many' so as to needlessly squander degrees of freedom. This is very useful in selecting among the variety of GARCH models.

In general, SBC has superior large sample properties and is asymptotically consistent, however: "in small samples, the AIC can work better than the SBC" (Enders, 2004). Using both AIC and SBC as a guide to model selection identifies two models: a minimum-AIC model, and a minimum-SBC model. If they 'disagree', SBC will always select a model with fewer parameters than will AIC. In many instances both criteria select the same model. "You can be quite confident in your results if both the AIC and SBC select the same model" Enders (2004).

In what follows, where AIC and SBC select different models that are both otherwise 'reasonable' (i.e. both meet the no ARCH criterion and the no redundant variables criterion), the model with lower standard error of the regression is chosen as 'best':

$$\text{standard error of regression} = \sqrt{\frac{RSS}{(T-k)}} \qquad (24)$$

Note that choosing between different minimum-AIC and minimum-SBC models in this way has some consistency with what AIC and SBC themselves seek to do, as it favours models with low *RSS* but also introduces some penalty for increasing the number of regressors k (increasing k in equation (24) will tend to inflate the standard error of the regression by reducing the denominator in equation (24) but will also tend to reduce *RSS* to an offsetting extent only if the additional variable has useful explanatory power).

5.7 Chapter Conclusions

This chapter has described the methods of analysis used. The main feature is estimation by the method of maximum likelihood (or quasi-maximum likelihood) of GARCH models consisting of two equations: a mean equation and a variance equation.

The mean equation in a GARCH model is the familiar CAPM or market model equation used in similar research by previous researchers as described in section 2.4 on p.10.

Kreander et al.'s (2005) introduction to the mean equation of the Henriksson and Merton (1981) specification for detecting market timing ability has been adopted and to this has been added the Treynor and Mazuy (1966) specification, the best fit in a particular case being selected (see section 5.2.2 on p.61).

Possible changes in mean equation parameters 'alpha' α_p or 'beta' β_p in reaction to an event such as fund FCE*'s adoption of ethical investment objectives (described in section 3.2 on p.26) can be captured using appropriately specified dummy variables (section 5.2.4 on p.66).

Estimation of such mean equations by ordinary least squares (OLS) provides reliable coefficient estimates but does not provide reliable information regarding whether or not these coefficients are statistically significantly different from zero. This is due to the presence of heteroscedasticity in the data, which violates an assumption underlying the OLS method. Previous researchers (e.g. Kreander et al., 2005) have used an amended 'robust' form of OLS estimation in order to address this problem.

Instead, the present research makes use of the fact that the heteroscedasticity present is of a particular form, auto-regressive conditional heteroscedasticity, or ARCH (section 5.3 on p.67). This ARCH can be explicitly modelled in the variance equation of a GARCH model, solving the estimation problem and also providing useful information. A variety of variance equation specifications have been proposed, including incorporation of a dummy variable to capture changes in conditional variance following FCE*'s adoption of ethical investment objectives (section 5.4 on p.73).

The variety of plausible mean equations and variance equations is such that it is helpful to carefully consider which are relevant in particular circumstances; with this in mind 'model sets' have been defined to meet particular analysis needs (section 5.5 on p.78).

Having identified a reasonable set of candidate models some means of selecting the 'best' for particular data is required. Three model selection criteria have been proposed: no residual ARCH, no redundant variables, and minimum AIC/SBC (section 5.6 on p.82).

Implementation of the no redundant variables criterion encounters a potential problem in that some data are not normally distributed, and the method of maximum likelihood typically used to estimate the GARCH models used here is sensitive to such departures from normality. In the present research this is dealt with by use of the 'Heteroscedasticity Consistent Covariance' (HCC) of Bollerslev and Wooldridge (1992) where required (section 5.6.2 on p.83).

Overall, these methods of analysis are consistent with those used by previous researchers, but also have a number of novel features.

The methods of analysis described in this chapter were implemented by means of batch programs run on Eviews 5.1 software. An example of such a batch program is provided in Appendix D on p.329.

6. Analysis I: Family Charities Ethical (FCE*)

6.1 Chapter Overview

This chapter reports on the analysis of ethical fund FCE* and its peers SUG, IUG, MCI and AAE described in chapter 3 from p.26 onwards using methods described in chapter 5 from p.60 onwards. FCE* is unusual in that it was launched as a conventional, non-ethical fund and later adopted ethical investment objectives in March-96. There was also a change in fund management in Sept-97.

Section 6.2 provides simple summary statistics, consideration of which suggests that the variance of FCE* may change over time somewhat differently from that of its peers.

Section 6.3 on p.91 examines the data for evidence of any change in the financial performance of FCE* from adoption of ethical investment in March-96 and also seeks to determine the duration of any such change.

Section 6.4 on p.95 repeats this exercise starting from the change in fund management in Sept-97. Comparing these two, it is concluded that the observed change in FCE*'s performance is better explained by the switch to ethical investment objectives than by the change in fund management.

Section 6.5 on p.98 extends the analysis to the four peers to investigate whether or not they display similar changes over these time periods; generally they do not.

Section 6.6 on p.103 repeats this analysis with an expanded the set of variance equation specifications.

Section 6.8 on p.106 concludes this chapter.

Prior research on FCE*, on which the present research builds, was recently published as Mill (2006) which is provided as Appendix E on p.346. Note that Mill (2006) makes use of the CAPM whereas the analysis here uses the market model. The main conclusions are robust to this change.

6.2 Summary Statistics

The methods of analysis described in chapter 5 from p.60 onwards are used below. However, a simple initial approach serves to illustrate some patterns in the data.

Table 6-1 shows the mean and standard deviation of monthly returns for FCE*, its four peers and for the FTSE All Share index (the benchmark of all five funds) over each of three sample periods: pre-March-96 (pre-ethical for FCE*), post-March-96 (post-ethical for FCE*), and for the entire period over which data was available from FCE*'s launch in May-82 to March-04.

In Table 6-1 the mean return to FCE* compares well with market index FTSE All and with the peers as in each of the three periods considered it has either the highest or second highest mean return. Mean returns for each fund are much lower post-March-96 than pre-March-96. But for only two funds (SUG and AAE), is the drop in mean return from pre- to post-March-96 statistically significant at the conventional 5% level. This implies that for the other funds (FCE*, IUG and MCI), the fall in sample mean is within the bounds of random sample variation – which is large.

Table 6-1 Summary statistics for FCE*, FTSE all-share and peers SUG, IUG, MCI and AAE

	FTSE All	FCE*	SUG	IUG	MCI	AAE
Mean						
entire period	1.173	1.267	1.175	1.031	1.051	1.117
pre-Mar-96[1]	1.534	1.584	1.721 *	1.230	1.427	1.556 *
post-Mar-96[1]	0.555	0.723	0.240 *	0.678	0.474	0.200 *
Standard Deviation						
entire period	4.655	4.970	5.213	4.673	4.588	4.926
pre-Mar-96[1]	4.826	4.948	5.694 **	4.993 *	4.880 *	5.284 *
post-Mar-96[1]	4.302	4.970	4.128 **	4.051 *	4.057 *	3.950 *

Note1: March-96 is the date of FCE*'s adoption of ethical investment principles

* = significant at 5% level ** = significant at 1% level

When considering the variability of returns, FCE* stands out as the only fund whose standard deviation does not drop to a statistically significant extent post-March-96.

In investment terms variability in returns is a measure of risk. There is a suggestion here that after adoption of ethical investment principles, FCE* may be more 'risky' relative to its peers and/or the market index. The remainder of this chapter is concerned with finding the 'correct' or best' GARCH model for each of FCE* and its four peers, in order to examine changes in variability over time more closely.

6.3 Duration of Ethical Event Dummy Variable

It was mentioned briefly in section 5.2.4 on p.66 that whereas the point in time at which ethical dummy variable D_t^E switches from zero to one is of course determined by FCE*'s adoption of ethical investment objectives in March-96, the duration of any effect is not known a priori. That is, one might specify D_t^E with a value of zero prior to March-96 and of 1 from March-96 until the end of the available data in March-04, or might have D_t^E return to a value of zero after a period of six months, or after a year, etc. Some means of determining this is required.

The following procedure was adopted. D_t^E was initially specified as having a value of 1 for six months after March-96 (i.e. Sept-96 = 1, thereafter D_t^E returns to zero). With this D_t^E specification, all mean equation specifications with and without D_t^E were estimated along with a GARCH(1,1) variance equation including D_t^E as a variance regressor and also without D_t^E as a variance regressor. This corresponds to model set M4 in Table 5-2 on p.80 consisting of 24 GARCH(1,1) models.

From these 24 six-month-duration models, the 'best' according to the model selection criteria in section 5.6 on p.82 was chosen.

The duration of ethical dummy variable D_t^E was then increased to 7 months, and the best 7-month-duration model chosen. Then 8 months, and so on until the end of the available data in March 2004 (a duration of 96 months from March-96).

The Akaike (AIC) and Schwarz (SBC) information criteria used for model selection (see section 5.6.3 on p.85) are also useful in distinguishing between models with varying durations of ethical dummy variable D_t^E. Figure 6-1 on p.92 shows the AIC and SBC of the 'best' model as ethical dummy variable duration is increased from 6 months upwards – a total of 90 different ethical dummy variable durations.

In Figure 6-1 on p.92 the trend is slightly obscured by unusually high information criteria at durations of 6, 7, 29, 30, 46 and 47 months. Nonetheless, both AIC and SBC initially display a clear downward trend (indicating an improving fit with the data) as dummy variable duration is increased beyond six months; this downward trend then reverses sharply.

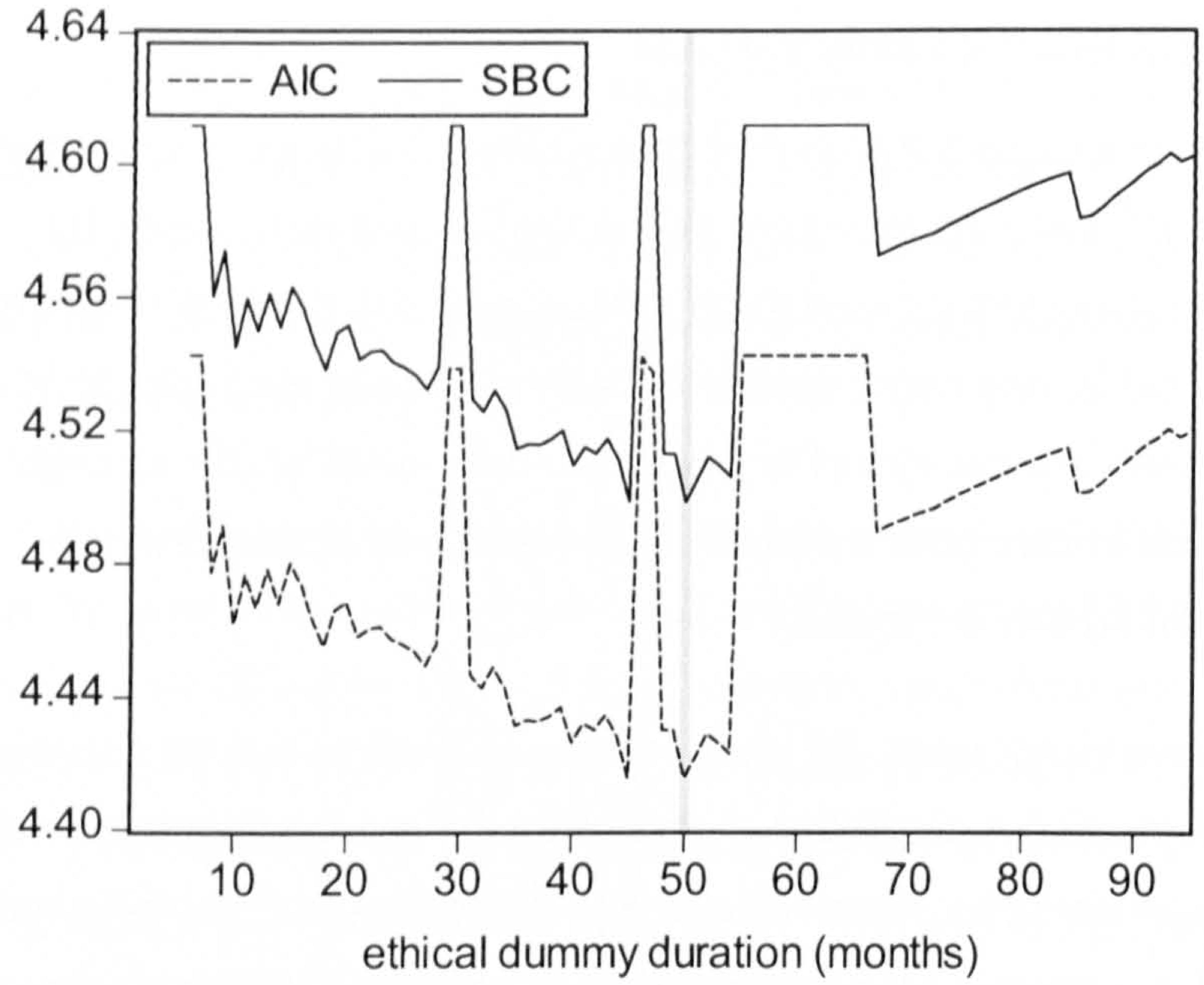

Figure 6-1 Information criteria as ethical dummy duration varies

For both AIC and SBC the minimum value occurs at a dummy variable duration of 50 months, shown by a vertical line in Figure 6-1, where AIC = 4.4154 and SBC = 4.4984. This represents an ethical dummy variable D_t^E duration from March-96 to May-00. It is reassuring to recall Enders' (2004) advice on the use of information criteria: "You can be quite confident in your results if both the AIC and SBC select the same model" – which here they do.

A similar exercise was conducted in previous research on FCE* published as Mill (2006) and provided as Appendix B on p.220. Mill (2006) uses the CAPM instead of the market model used in the present research. The results were quite similar, with an ethical dummy variable length of March-96 to Jan-00, rather than May-00, being selected.

Estimation output for the selected dummy variable duration of March-96 to May-00 in the present research is shown in Table 6-2.

Table 6-2 'Best' FCE* model with ethical dummy duration 50 months

		Coefficient	Estimate	p-value	HCC-p	Q-stat	LM
R-sq	0.7637	α_p	0.0499	0.0069	0.6487	0.091	0.093
RSS	2.4677	β_p	0.9309	0.0000	0.0000	0.098	0.079
AIC	4.4154	γ_0	0.1027	0.0002	0.0001	0.108	0.120
SBC	4.4984	γ_1	-0.0587	0.0012	0.0425	0.186	0.196
J-Bera	0.7258	δ_1	1.0226	0.0000	0.0000	0.225	0.277
		γ_E	0.4883	0.0000	0.0000	0.296	0.335

In interpreting and assessing such GARCH models use is made of information that is not presented together in a concise format by the Eviews 5.1 software used here (or by any similar software). Since comparing many somewhat similar GARCH models is the main focus of the present research, the relevant information for each model has been tabulated in a simple, convenient and consistent format, as follows.

The first two columns of Table 6-2 on p.93 list simple summary information. Firstly, the coefficient of determination (R^2). Then three items used in model selection: the standard error of the regression (*RSS*) as per equation (24) on p.86, and the Akaike (AIC) and Schwarz (SBC) information criteria (see section 5.6.3 on p.85).

The fifth item listed on the left of Table 6-2 – "J-Bera" – is the p-value summarising the result of a Jarque-Bera test (Bera and Jarque, 1980) of the normality of the standardised residuals (see equation (21) on p.84). As described towards the end of section 5.6.2 on p.83, the result of this test determines whether, in assessing the statistical significance of the estimated coefficients, usual maximum likelihood standard errors and p-values or the alternative Bollerslev and Wooldridge (1992) 'Heteroscedasticity Consistent Covariance' (HCC) standard errors and p-values should be used.

The next section of Table 6-2 begins with columns headed "Coefficient" and "Estimate" listing the relevant coefficients along with their estimated values. Mean equation parameters are listed first – here α_p and β_p as per equation (4) on p.66 – followed by variance equation parameters γ_0, γ_1, δ_1 and γ_E as specified in equation (13) on p.75.

Two sets of p-values are provided in the next two columns headed "p-value" and "HCC-p". In the maximum likelihood (or quasi-maximum likelihood) estimation used here, whether or not an individual coefficient is statistically significantly different from zero is judged with reference to a z-test. The first, "p-value", column lists the usual maximum likelihood p-values, while the second, "HCC-p" column, lists Bollerslev and Wooldridge (1992) HCC p-values.

Which of these is relevant in a particular case depends on the result of the Jarque-Bera test. Here, with $p = 0.7258$ the Jarque-Bera null hypothesis of normality of standardised residuals is not rejected at the conventional 5% level, and so the usual maximum likelihood p-values are appropriate (in the column headed "p-value"). (For other funds and/or other data periods, it can happen that Jarque-Bera $p < 0.05$ and the "HCC-p" p-values must be used.)

The final two columns of Table 6-2 on p.93 headed "Q-stat" and "LM" report the p-value results from ARCH tests as described in sections 5.3.2 and 5.3.3 on pages 70 and 71. The point to note is that all p-values in these columns are above the conventional 5% level, so that the null hypothesis of no ARCH is not rejected – i.e. the ARCH has successfully been modelled (compare the results of tests for FCE* using an OLS model over the same time period in Table 5-1 on p.72).

Examining the coefficient estimates in Table 6-2 two things are notable.

Firstly, the coefficient on ethical dummy variable γ_E is positive, large (0.4883) and highly statistically significant ($p = 0.0000$), confirming that there is a temporary increase in conditional variance following FCE*'s adoption of ethical investment objectives.

Secondly, FCE* has a small positive 'alpha' α_p of 0.0499 that is highly statistically significant ($p = 0.0069$). This indicates superior performance relative to the market index. The 'alpha' α_p estimate obtained using other methods differs from this, as shown in Table 6-3.

Table 6-3 FCE* alpha estimate by different methods

Model		'alpha' α_p	p-value
A	GARCH(1,1) with ethical dummy D_t^E	0.0499	0.0069
B	GARCH(1,1) no dummy	0.1228	0.3502
C	OLS (no correction)	0.1873	0.2342
D	OLS (White correction)	0.1873	0.2176
E	OLS (Newey and West correction)	0.1873	0.2171

In Table 6-3, model A repeats the relevant information from Table 6-2 on p.93 above. Model B reports the 'alpha' α_p estimate obtained from a GARCH(1,1) model that ignores the possibility of a step change in conditional variance from March-96, i.e. with no ethical dummy variable γ_E. Although 'alpha' is relatively large, it is not statistically significantly different from zero, so that there is no evidence of superior financial performance by FCE*.

Model C reports the 'alpha' α_p estimate obtained from a simple OLS model, and again this is not statistically significantly different from zero. Even in model D, which uses White's (1980) p-values that are robust to heteroscedasticity, essentially the same result is obtained. Likewise model E which uses Newey and West (1987) p-values, robust to heteroscedasticity and autocorrelation (as used by Kreander et al. (2005)). This illustrates the importance of using the 'correct' model, as the conclusions reached can be quite different, even using 'robust' estimation methods.

In addition to estimating the optimal ethical dummy variable duration, this exercise provides evidence against the possibility that there may be a change in intercept ('alpha' α_p) or slope ('beta' β_p) of the mean equation for FCE* from the time of adopting ethical investment principles, as follows.

From the 24 models 'on offer' in model set M4 in Table 5-2 on p.80, for 84 of the 90 dummy durations shown in Figure 6-1, AIC and SBC select the same 'best' model with no mean-equation intercept or slope dummy, but with a variance dummy. Of the remaining six possible durations (corresponding to the unusually high information criteria in Figure 6-1) in four cases the alternative model is GARCH(1,1) with no mean equation dummies. In only two cases (durations of 29 and 30 months) is a model with a slope ('beta' β_p) dummy selected by the Akaike information criterion (AIC); but for these two months the Schwarz criterion (SBC) 'disagrees' selecting a GARCH(1,1) model with no mean equation or variance equation dummies.

6.4 Duration of Management Event Dummy Variable

An entirely similar exercise was conducted to determine the duration of management dummy variable D_t^M, starting from the management change in September 1997. This involved estimating and selecting from the 24 GARCH(1,1) models in model set M5 in Table 5-2 on p.80 i.e. those models that either do or do not feature a management event dummy variable in some way.

The results are summarised in Figure 6-2. Both information criteria have clear minima after 29 months when AIC = 4.4334 and SBC = 4.5442. The corresponding management dummy duration is from Sept-97 to Feb-00.

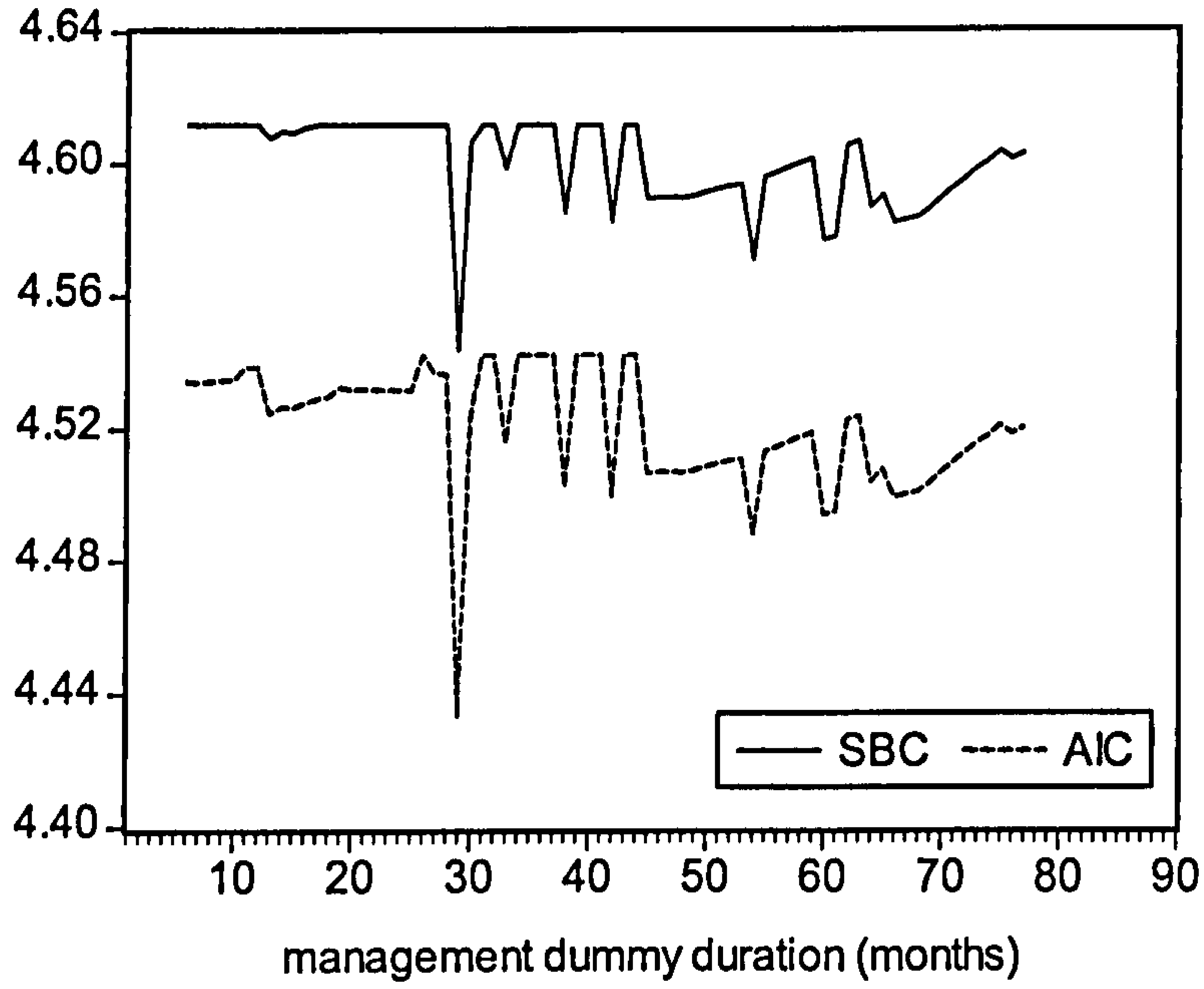

Figure 6-2 Information criteria as management dummy duration varies

Estimation output for the model selected as 'best' using this management dummy variable is shown in Table 6-4.

Table 6-4 'Best' FCE* management dummy model with duration 29 months

		Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7687	α_p	0.0673	0.2787	0.5540	0.056	0.057
RSS	2.4513	a^M	1.1298	0.0454	0.0517	0.133	0.116
AIC	4.4334	β_p	0.9265	0.0000	0.0000	0.140	0.149
SBC	4.5442	b^M	-0.3164	0.0008	0.0202	0.182	0.160
J-Bera	0.8949	γ_0	0.1354	0.0000	0.0057	0.238	0.250
		γ_1	-0.0607	0.0000	0.0011	0.289	0.282
		δ_1	1.0189	0.0000	0.0000	0.241	0.274
		γ_M	0.8011	0.0000	0.0000	0.282	0.213

Interpretation of Table 6-4 is as described for Table 6-2 on p.92 above, except that the mean equation in Table 6-4 now includes two new coefficients: a^M and b^M and also now in the variance equation ethical dummy coefficient γ_E is replaced by management dummy coefficient γ_M. New mean-equation coefficients a^M and b^M measure the effect of any change in 'alpha' α_p and in 'beta' β_p, respectively, from the time of the change in fund management as in equations (5) and (6) on pages 66 and 67.

If the results in Table 6-4 are accepted, they imply that for a period of 29 months following the fund management change, not only was there a step increase in conditional variance (large and positive γ_M of 0.8011) but also a large temporary increase in 'alpha' α_p (large and positive a^M of 1.1298) and corresponding fall in 'beta' β_p (large and negative b^M of -0.3164).

However, comparing Table 6-2 with Table 6-4, it is reasonably clear that the ethical dummy model in Table 6-2 is a better fit with the FCE* data than is the management dummy model in Table 6-4. This is partly, but not entirely, because both AIC and SBC information criteria are lower in the case of the ethical dummy model (which is preferable), providing a clear quantitative result.

There are also three other less definitive arguments that contribute to preferring the ethical dummy model over the management dummy model.

Firstly, comparing Figure 6-1 on p.92 (ethical dummy) with Figure 6-2 on p.96 (management dummy), the latter lacks the former's broad trend of decrease followed by increase as though modelling a phenomenon more and then less accurately. Instead Figure 6-2 is broadly horizontal with a single unusually low minimum that may be a random, chance result.

Secondly, the first-order ARCH test p-values of 0.056 and 0.057 in Table 6-4, although above the conventional 5% threshold for statistical significance, are rather close to it.

And thirdly, the 'best' management dummy model results in Table 6-4on p.96 are a little implausible. They suggest that for a period of just over two years following the management change FCE* took on less market risk ('beta' β_p describing its covariance with the market index was reduced by around one third from 0.9265 to 0.6101) which in equilibrium would suggest lower mean returns, while also random variation around the market index increased (indicated by γ_M of 0.8011) yet at the same time there was a very large increase in mean return by an amount indicated by a^M = 1.1298.

From the above it is tempting to conclude that there is indeed a temporary increase in FCE*'s conditional variance that is due to its adoption of ethical investment objectives and not to the change in fund management.

However, there is a further step in the argument. Having specified the optimal dummy variable length corresponding to the two most plausible 'internal' explanations for the observed temporary increase in the variability of FCE* returns, these models can also be estimated for each of the four FCE* peers.

If the phenomenon under investigation is internal to FCE* and not a market-wide effect then the two dummy variables should have no explanatory power for the four peers i.e. the 'best' model for each of the four peers should include neither an ethical nor a management dummy variable in the mean or the variance equation.

6.5 FCE* and Peers: GARCH(1,1) Results

Now the 45 models in model set M3 in Table 5-2 on p.80 are estimated for each of FCE*'s four peers funds and the 'best' chosen according to the criteria in section 5.6 on p.82. Model set M3 includes all GARCH(1,1) model variants that include an ethical dummy variable or management dummy variable in the mean and/or variance equations, and all those with no dummy variable.

The dummy variable durations are as determined in preceding sections 6.3 and 6.4 on pages 91 and 95 i.e. the ethical dummy is from March-96 to May-00 and the management dummy is Sept-97 to Feb-00.

Table 6-5 on p.99 shows the results obtained. (For FCE* Table 6-5 simply repeats the information in Table 6-2 on p.92 above, for convenience). Interpretation of Table 6-5 on p.99 is as described for Table 6-2 on p.92 above.

FCE*'s statistically significant and positive 'alpha' α_p of 0.0499 implies mean returns superior to its four peers, none of which has α_p statistically significantly different from zero. This is the case both before and after the adoption of ethical investment, as indicated by the absence of an intercept dummy variable a^M (equations (5) and (6) on pages 66 and 67) for FCE* in Table 6-5 on p.99 (the model shown was chosen as a better fit to the data than alternative models including such an intercept dummy variable). By similar reasoning, 'beta' β_p is also unchanged by the change in investment objectives.

Table 6-5 'Best' GARCH(1,1) models for FCE* and four peers

Fund: FCE*

		Coefficient	Estimate	p-value	HCC-p	Q-stat	LM
R-sq	0.7637	α_p	0.0499	0.0069	0.6487	0.091	0.093
RSS	2.4677	β_p	0.9309	0.0000	0.0000	0.098	0.079
AIC	4.4154	γ_0	0.1027	0.0002	0.0001	0.108	0.120
SBC	4.4984	γ_1	-0.0587	0.0012	0.0425	0.186	0.196
J-Bera	0.7258	δ_1	1.0226	0.0000	0.0000	0.225	0.277
		γ_E	0.4883	0.0000	0.0000	0.296	0.335

Fund: SUG

		Coefficient	Estimate	p-value	HCC-p	Q-stat	LM
R-sq	0.6836	α_p	-0.0275	0.8244	0.8404	0.444	0.448
RSS	2.9547	β_p	0.9109	0.0000	0.0000	0.163	0.158
AIC	4.7694	γ_0	-0.0411	0.0544	0.0228	0.287	0.295
SBC	4.8387	γ_1	0.0406	0.0076	0.0525	0.251	0.218
J-Bera	0.3957	δ_1	0.9599	0.0000	0.0000	0.275	0.250
						0.177	0.204

Fund: IUG

		Coefficient	Estimate	p-value	HCC-p	Q-stat	LM
R-sq	0.9078	α_p	0.0507	0.4440	0.4741	0.553	0.556
RSS	1.4357	β_p	0.9444	0.0000	0.0000	0.838	0.851
AIC	3.3924	γ_0	0.0032	0.5416	0.6452	0.052	0.058
SBC	3.4667	γ_1	-0.0251	0.0690	0.2769	0.097	0.093
J-Bera	0.9201	δ_1	0.0173	0.0000	0.0000	0.146	0.147
						0.214	0.171

Fund: MCI

		Coefficient	Estimate	p-value	HCC-p	Q-stat	LM
R-sq	0.9171	α_p	-0.0531	0.4691	0.4665	0.165	0.168
RSS	1.3349	β_p	0.9299	0.0000	0.0000	0.260	0.233
AIC	3.3495	γ_0	-0.0417	0.0000	0.2385	0.349	0.340
SBC	3.4350	γ_1	0.0120	0.2405	0.6198	0.505	0.483
J-Bera	0.1348	δ_1	1.0041	0.0000	0.0000	0.472	0.487
		γ_E	0.0534	0.0000	0.0005	0.590	0.584

Fund: AAE

		Coefficient	Estimate	p-value	HCC-p	Q-stat	LM
R-sq	0.8360	α_p	-0.1041	0.4244	0.4081	0.441	0.444
RSS	2.0123	β_p	0.9566	0.0000	0.0000	0.514	0.499
AIC	4.2132	γ_0	0.3604	0.2280	0.2744	0.296	0.334
SBC	4.2868	γ_1	0.0866	0.0775	0.1357	0.185	0.237
J-Bera	0.7567	δ_1	0.8238	0.0000	0.0000	0.050	0.065
						0.035	0.074

With a single exception, all Q-statistic and ARCH LM p-values in the final two columns of Table 6-5 on p.99 are always > 0.05 indicating a failure to reject the null hypothesis of 'no ARCH' (see section 5.3.2 on p.70 and section 5.3.3 on p.71 for details). Thus the GARCH(1,1) model does adequately capture the ARCH that is present for all funds but one.

The single exception is the 7^{th}-order Q-statistic p-value of 0.035 for fund AAE at the bottom of Table 6-5. None of the other 44 GARCH(1,1) specifications in model set M3 in Table 5-2 on p.80 (allowing for market timing, ethical or management dummy variables, etc.) could improve on the results shown in Table 6-5. This suggests that fund AAE may be more accurately modelled using one of the alternative variance equation specifications described in section 5.4 from p.73 onwards (which proves to be the case, see below). (Note, however, that had Q-stats been calculated up to, say, the fourth order, no problem would have been apparent.)

It was argued above that if the phenomenon under investigation is internal to FCE* (e.g. its adoption of ethical investment objectives), then the 'best' model for each of the four peers SUG, IUG, MCI and AAE should include neither an ethical nor a management dummy variable in the mean or the variance equation i.e. γ_E and γ_M should not appear in Table 6-5. This is not quite what is found.

While γ_E is absent from peers SUG, IUG and AAE, γ_E does appear in the variance equation of peer MCI, albeit with a much smaller coefficient of 0.0534 compared to 0.4883 for FCE*. Both occurrences of γ_E in Table 6-5 are shaded for emphasis.

Further information can be gained by examination of the estimated conditional standard deviation that the coefficients in Table 6-5 represent.

As expected, Figure 6-3 on p.101 for FCE* shows a sharp rise in conditional standard deviation above previous levels for the duration of ethical dummy variable D_t^E from March-96 to May-00, shown shaded in Figure 6-3 on p.101.

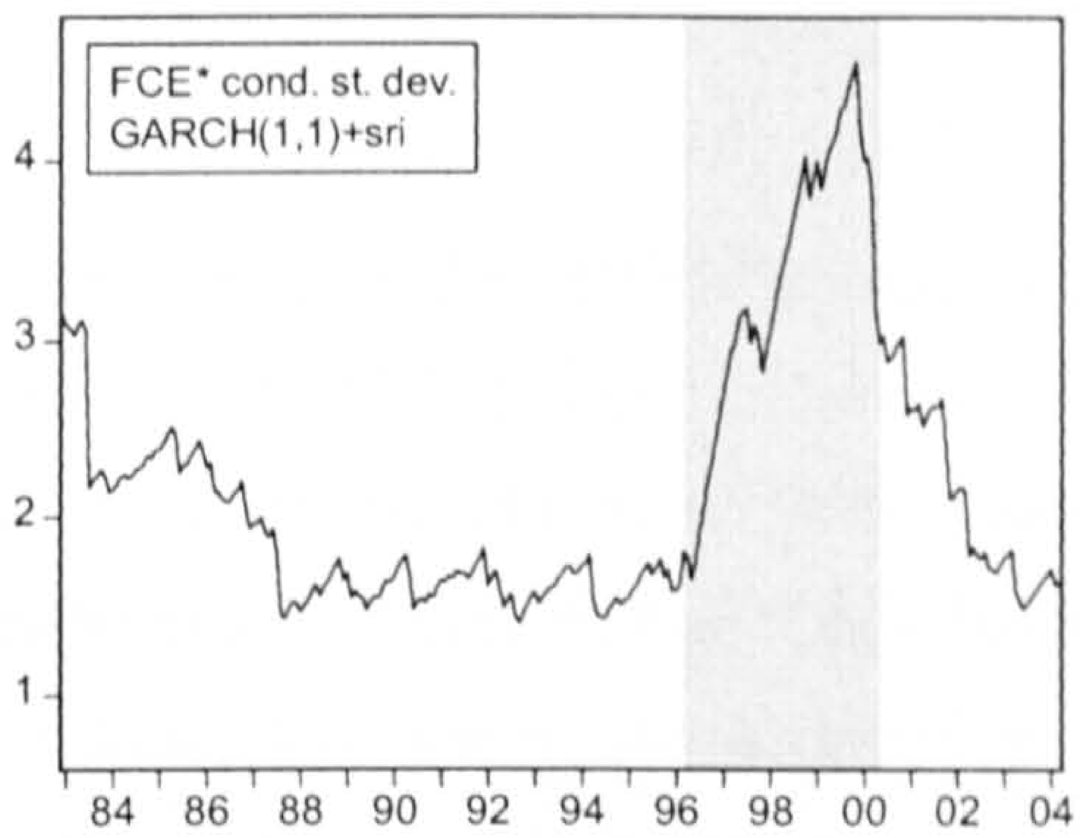

Figure 6-3 FCE* Conditional Standard Deviation (GARCH(1,1))

Figure 6-4 shows estimated conditional standard deviation for the four peers, with the duration of D_t^E again shaded. It is quite clear that, as expected, the shaded region has no particular significance in the evolution of conditional standard deviation of the three peers having no dummy variable D_t^E in Table 6-5: SUG, IUG and AAE. For peer MCI, however, conditional standard deviation changes abruptly in the shaded region.

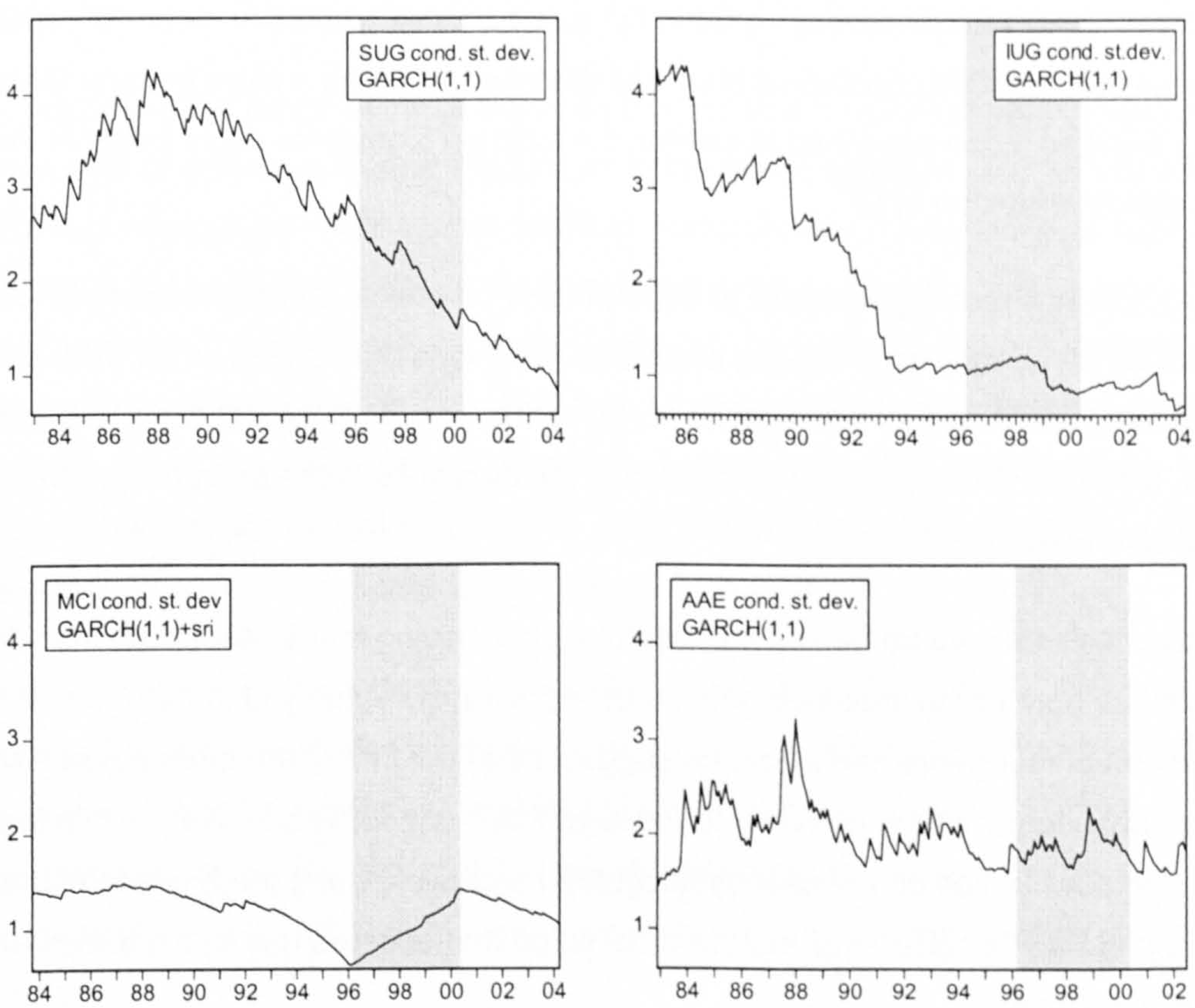

Figure 6-4 SUG, IUG, MCI, AAE Conditional Standard Deviation (GARCH(1,1))

Comparing Figure 6-4 with Figure 6-3, three explanations of MCI's conditional standard deviation seem possible.

Firstly, (since MCI is certainly not reacting to the change in FCE* investment principles) MCI may be reacting to some other event or cause that happens by chance to coincide with the timing of FCE*'s adoption of ethical investment. Such a cause or event may be internal to MCI, affecting only MCI, or external to MCI and therefore presumably likely to also affect other similar funds. If such an external cause or event might also influence FCE* then this would cast doubt on the conclusion that the observed sharp increase in FCE*'s conditional standard deviation is due to its adoption of ethical investment and not some other cause. However, the fact that there is no corresponding change in the conditional standard deviation of peers SUG, IUG and AAE (which can equally well be viewed as peers of MCI or of FCE*) suggests that any such event is internal to MCI and not responsible for any change in the conditional standard deviation of FCE*.

Secondly, the GARCH(1,1) model used in the above may be unnecessarily restrictive, and inclusion of ethical dummy variable D_t^E may help this restrictive model to capture the evolution of MCI's conditional standard deviation whereas a more general GARCH model such as those described in section 5.4 from p.73 onwards might better fit the data without inclusion of D_t^E.

Thirdly, the statistical significance of coefficient γ_E on ethical dummy variable D_t^E may be due simply to random sampling error (at 0.0534 γ_E is after all not so far from zero). When using conventional significance levels of 5%, one must expect this to happen at times, although of course not only this result but all results in the present research are vulnerable to this.

The discussion above underlines the usefulness of having four peers rather than the one unique peer of the 'matched pair' method previously employed in this field. With the benefit of four peers, the evidence suggests that the first of the three possibilities above (an external cause or event common to FCE* and MCI) is unlikely, while the other two possibilities do not directly affect the conclusion that a there is a temporary increase in FCE*'s conditional standard deviation that appears due to the switch to ethical investment.

6.6 FCE* and Peers: GARCH Variant Results

The analysis in the preceding section uses model set M3 (see Table 5-2 on p.80). Model set M3 does not explore the full range of possible conditional variance models described in section 5.4 from p.73 onwards, opting instead for the 'one-size-fits-all' GARCH(1,1) specification, as the Eviews 5.1 software simply crashed when model set M2 with its 3015 models was attempted.

However, it is clear from the above that models incorporating mean-equation intercept and slope dummies (as in equations (5) and (6) on pages 66 and 67) do not fit the particular data used here well – they are consistently rejected by the selection criteria in favour of more parsimonious models without such mean-equation dummy variables. This is evident in Table 6-5 on p.99 where no 'best' model for any of the five funds includes such a variable. The same can also be said of market timing, as in equations (2) and (3) on p.63. No 'best' models in Table 6-5 on p.99 include market timing. However, market timing is a generally observed phenomenon in fund performance research, so that retaining this possibility in the model set seems appropriately cautious.

By restricting the range of mean-equation models to a smaller range of possibilities – those with or without a market timing term in the mean equation, and with or without an ARCH-in-mean term – it becomes possible, using Eviews 5.1 software, to explore the full range of conditional variance models described in section 5.4 from p.73 onwards. This produces model set M1, shown in Table 5-2 on p.80 to contain 201 models. These 201 models are each estimated twice, both with and without ethical dummy variable D_t^E as a regressor in the variance equation (equal to one from March-96 to May-00, as best fits ethical fund FCE*). From these 402 models, the 'best' is again selected according to the criteria in section 5.6 on p.82.

Remarkably, when this is done, for four of the five funds: FCE*, SUG, IUG and MCI, exactly the same GARCH(1,1) model is selected as when this was the only option. For these four funds the results are exactly the same as those shown in Table 6-5. This provides support for Brooks' (2002) view, referred to above in section 5.4.1on p.73 that "in general a GARCH(1,1) model will be sufficient to capture the volatility clustering in the data".

Note that one of the unchanged funds is MCI. In discussing Figure 6-4 on p.101, three possible explanations were considered for the MCI result. The second possible explanation – that the GARCH(1,1) specification was unduly restrictive, and that a more general model may fit the data better without incorporating the ethical dummy variable as a regressor – has now been shown not to be the case.

Only for peer fund AAE is a more sophisticated GARCH variant model selected. This is consistent with the 7th-order Q-statistic p-value of 0.035 for fund AAE at the bottom of Table 6-5 on p.99. The improved model is the component GARCH, or CGARCH model of Engle and Lee (1993a, 1993b) and Engle and Mezrich (1995) described by equations (18) and (19) on p.77. The results are shown in Table 6-6 on p.104.

It is notable that whereas 'alpha' α_p for AAE in Table 6-5 on p.99 was not statistically significantly different from zero, in the improved model in Table 6-6 on p.104 α_p is now highly statistically significant, and being negative this implies under-performance relative to the market benchmark. This sensitivity of 'alpha' α_p estimates to the way in which conditional variance is modelled was also encountered with FCE* as illustrated in Table 6-3 on p.94, and would seem to have important implications for fund performance research.

Table 6-6 'Best' GARCH variant model peer AAE

		Coefficient	Estimate	p-value	HCC-p	Q-stat	LM
R-sq	0.8305	α_p	-0.3674	0.0000	0.0000	0.279	0.283
RSS	2.0545	β_p	0.9433	0.0000	0.0000	0.495	0.479
AIC	4.1610	γ_0	3.6992	0.5377	0.5036	0.268	0.298
SBC	4.2640	ρ	0.9964	0.0000	0.0000	0.378	0.440
J-Bera	0.6273	Φ	0.0523	0.0016	0.0127	0.384	0.441
		γ_1	0.1144	0.0000	0.0000	0.149	0.254
		δ_1	-1.0108	0.0000	0.0000	0.184	0.324

The conditional standard deviation of AAE estimated in Table 6-6 is illustrated in Figure 6-5.

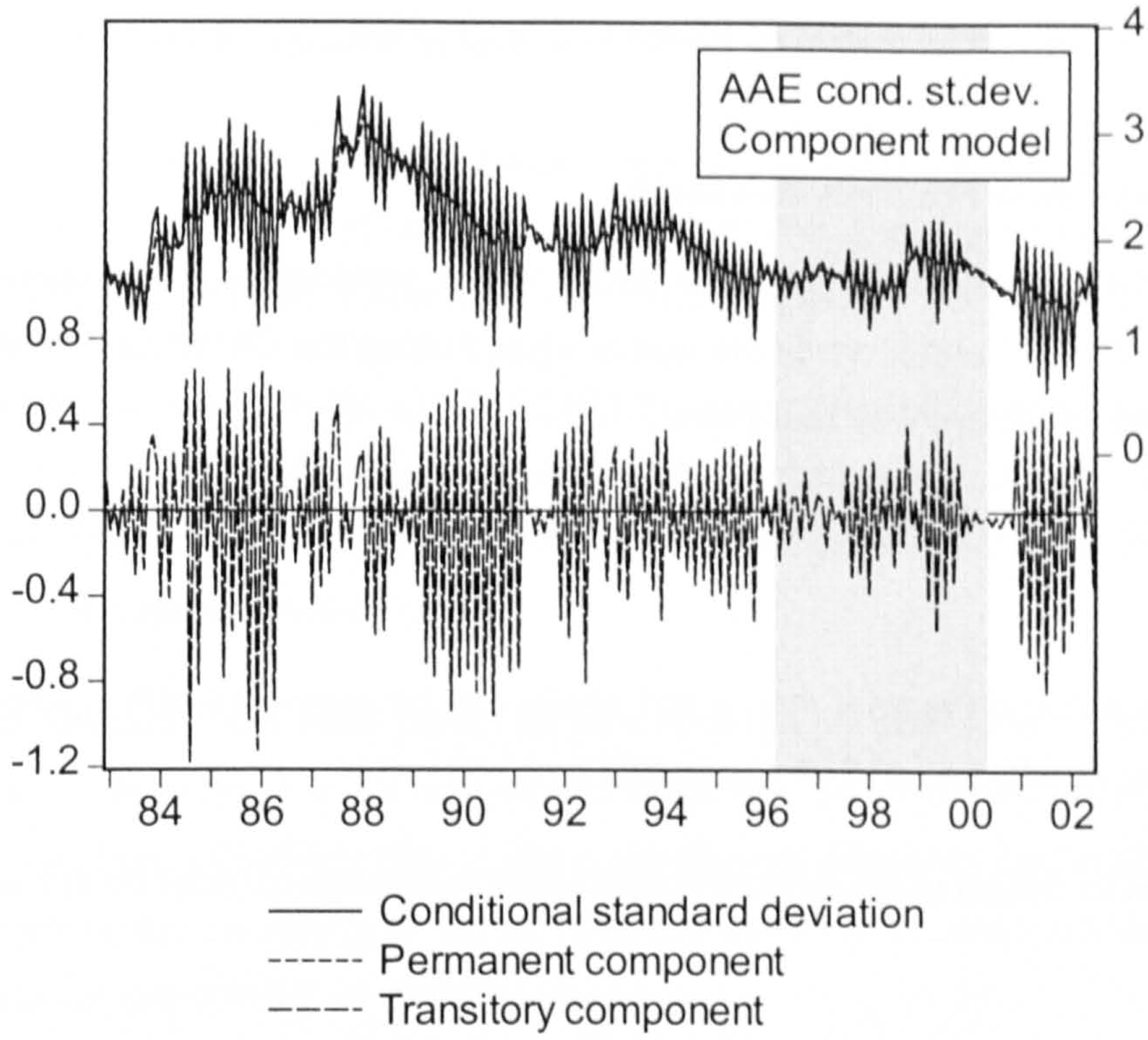

Figure 6-5 AAE Conditional Standard Deviation (CGARCH version)

In Figure 6-5 the conditional standard deviation, shown as a solid line in the upper panel, is decomposed into two components. The permanent component is a 'smoothed' dashed line in the upper panel. The transitory component consists of the higher-frequency deviations around this permanent component, which are shown in more detail in the lower panel.

While Figure 6-5 provides considerably more detail than the GARCH(1,1) version illustrated in the lower right of Figure 6-4 on p.101, and the improved model provides a quite different 'alpha' α_p estimate, in terms of comparison with FCE*'s conditional variance the conclusion is very similar. AAE's conditional standard deviation peaks at a value of 3 or so around 1988 and is otherwise around a value of 2 or so. The ethical dummy period from March-96 to May-00 (shaded in Figure 6-5) appears to have no particular relevance, although the transitory component has a 'quiet period' extending from somewhat before this to somewhat later than this.

Therefore, while more detailed modelling of AAE's returns has provided a more accurate view of AAE's financial performance it has not altered the conclusion that the temporary increase in FCE*'s variance between March-96 and May-00 appears limited to FCE* and so is likely to be due to its switch to ethical investment objectives.

6.7 Comparison With Previous Research

The results above are very similar to those in Mill (2006), provided here as Appendix E on p.346, in which FCE* and three peers was analysed using the CAPM as opposed to the market model used here with four peers.

To see this, Table 6-5 on p.99 above can be compared with Table IV on p.356 of Appendix E.

Likewise, Figure 6-3 and Figure 6-4 on p.101 above can be compared with Figures 3, 4, 5 and 6 on pages 356 and 357 of Appendix E.

Such robustness to choice of equilibrium model helps to provide confidence in the results.

6.8 Chapter Conclusions

Following adoption of ethical investment objectives the variability of ethical fund FCE* about the market index increases for a period of just over four years (50 months) from March-96 to May-00 (section 6.3 on p.91).

A GARCH model incorporating this temporary increase in FCE*'s variability also estimates 'alpha' α_p as positive and statistically significantly different from zero, whereas alternative models do not. Estimates of 'alpha' α_p appear to be sensitive to the correct modelling of conditional variance in ways not captured by the 'robust' OLS approach adopted by previous researchers (Table 6-3 on p.94).

An alternative explanation for FCE*'s period of increased variability – that it is due to a change in fund management in Sept-97 – is not well supported by the data (section 6.4 on p.95).

An alternative explanation that the period of increased variability of FCE* arises from events or causes external to FCE* rather than to the internal change in investment objectives, is also not well supported by the data. If this were so, a similar change might be expected to be observed in the four peers. No similar change was observed in FCE*'s peers (section 6.5 on p.98).

In reaching the previous conclusion, it was found to be considerably beneficial to have four peers with which to compare FCE* rather than the single peer used by previous researchers (section 6.5 on p.98; for previous research see section 2.4 on p.10).

Initially the 'one-size-fits-all' GARCH(1,1) variance equation specification was imposed. From a full range of variance equation specifications four out of five funds continued to select GARCH(1,1) as 'best', supporting the widespread view that GARCH(1,1) is often adequate (section 6.6 on p.103).

The revision of the 'best' model for fund AAE did not affect the main conclusion of this chapter regarding FCE*'s post-ethical variability. But the estimate of 'alpha' α_p was revised from effectively zero to being significantly negative, confirming the point above regarding the sensitivity of 'alpha' α_p estimates to the correct modelling of conditional variance (section 6.6 on p.103).

The results of the present research using the market model are in good general agreement with previous research reported in Mill (2006) using the CAPM (see Appendix B on p.220). Such robustness to choice of model helps to provide confidence that the phenomenon is 'real' rather than, say, a spurious effect of random sampling error.

7. Analysis II: Twelve Ethical Funds

7.1 Chapter Overview

This rather long chapter presents results from the analysis of the dozen ethical funds and their peers described in chapter 4 from p.34 onwards.

Sections 7.2 through to section 7.13 on p.164 report on each ethical fund in turn, in order of launch date. In each case all 201 GARCH variant models in model set M1 (see Table 5-2 on p.80) are considered over all relevant 'time samples' (see section 4.6 on p.51). Results using both the market model and the capital asset pricing model are provided (discussed in section 5.2.3 on p.64), calculated using each fund's own nominated benchmark index (see section 4.5.2 on p.46 as discussed in section 2.4.1 on p.10) and also using the broad FTSE All Share market index.

Sections 7.2 to 7.13 contain a large quantity of detailed and diverse results, making a concise summary desirable. This is provided in a necessarily somewhat over-simplified form in section 7.14 on p.167.

Section 7.15 on p.170 uses the preceding fund-by-fund results to examine whether, despite the diversity amongst the dozen ethical funds, any generalisations regarding financial performance can be made about the ethical funds as a group.

Section 7.16 on p.176 presents a cross-sectional regression similar to that employed by previous researchers (Gregory et al., 1997; Kreander et al., 2005) investigating possible associations between financial performance and fund age or fund size, for ethical funds and their peers.

Section 7.17 on p.183 concludes the chapter.

7.2 ISG* ISIS Stewardship Growth Results

7.2.1 ISG* Mean Returns – 'Alpha' α_p

Table 7-1 provides summary information regarding how the mean performance of ISG* compares both to the benchmark index and to its peers, making use of 'alpha' α_p, described in section 5.2 on p.61.

Both the market model of equation (4) on p.66 and the CAPM of equation (1) on p.62 were discussed in in section 5.2 on p.61. Market model results are to the left in Table 7-1; CAPM results are presented for comparison to the right. In the fund-by-fund reports that follow below, generally market model results are discussed[1]. Summary results for both the market model and the CAPM are provided in Table 7-25 and Table 7-26 on p.168.

Table 7-1 ISG* and Peers: Comparing 'Alpha' α_p

		MARKET				CAPM			
		ISG*	ISG* p	peers	anova p	ISG*	ISG* p	peers	anova p
OWN	all	0.095	0.367	0.048	0.908	-0.047	0.660	0.118	0.664
	ind	0.095	0.367	0.013	0.641	-0.047	0.660	0.127	0.752
	x4	0.164	0.000	-0.062	0.764	0.257	0.054	-0.055	0.658
	x8	0.392	0.007	0.081	0.268	0.021	0.353	-0.204	0.761
	x12	-0.021	0.832	-0.041	0.923	-0.132	0.186	0.145	0.686
FTSE	all	0.560	0.000	0.048	0.266	0.382	0.095	0.118	0.497
	ind	-2.174	0.000	0.013	0.001	0.210	0.358	0.127	0.878
	x4	0.505	0.032	-0.062	0.470	0.351	0.057	-0.055	0.569
	x8	0.409	0.023	0.081	0.248	0.623	0.000	-0.204	0.308
	x12	0.350	0.005	-0.041	0.133	0.241	0.100	0.145	0.887

Summary information on ethical fund ISG* and its four peers JPE, IPU, SMU and AUG was provided in Table 4-3 on p.46. There it can be seen that whereas ISG* has the Hoare Govett smaller companies index as benchmark, the four peers have the FTSE All Share index.

Accepting the need for 'like-for-like' comparisons, two possible interpretations of 'like-for-like' are considered in Table 7-1. The upper potion of Table 7-1 reports on analysis in which the particular benchmark of each fund is used on an individual basis. This is reasonable since this compares each fund with the index that the fund managers declare as most relevant, but here, for example, means that ISG* is assessed with

[1] The focus on the market model in preference to the CAPM in this chapter is a little exaggerated and requires qualification. The market model is a useful alternative when considering variability, but for mean returns the CAPM is arguably more appropriate as it allows for the availability of lending and borrowing at a risk-free rate. However, overall conclusions are not greatly affected by the choice of CAPM or market model, as demonstrated by the close similarity between summaries in Table 7 25 and Table 7 26 on p.167.

respect to a different benchmark to its four peers. For comparison, the lower portion of Table 7-1 reports results in which the FTSE All Share index is used as the measure of market return for every fund, irrespective of its stated benchmark.

Five 'time samples' were established in section 4.6 on p.51 in order to make efficient use of the available data and to provide some indication of the robustness of the results. Table 7-1 also reports estimates over each of these five 'time samples': 'all', 'ind', 'x4', etc.

Within each quadrant in Table 7-1 (market – own, CAPM – FTSE), etc.) four columns of results are reported, all relating to parameter 'alpha' α_p. The first column, labelled "ISG*" reports the estimated α_p of ethical fund ISG*, while the second column, labelled "ISG* p" reports the p-value from a z-test of the null hypothesis that this sample estimate is from a population with mean equal to zero. Rejection of this null hypothesis (at the conventional 5% level of significance) is evidence either of performance superior to the benchmark index (if 'alpha' α_p is positive) or inferior (if negative).

In each quadrant in Table 7-1 the third column, labelled "peers" reports the mean value across the four peers of the estimated 'alpha' α_p of the peer funds. Recalling that in this instance each of the four peers has the FTSE All Share index as its 'own' index, note that the lower five entries in this column simply repeat the upper five entries.

Next is "anova p" the result of an 'analysis-of-variance' t-test for equality of mean α_p between ISG* and the four peers. At the conventional 5% significance level, $p < 0.05$ here would indicate that ISG*'s performance, as measured by 'alpha' α_p, is significantly better or worse than that of its four peers. In Table 7-1 these p-values are generally high, not unexpectedly, since this test has little power (i.e. small probability of correctly rejecting a false null hypothesis) in a small sample size of only five funds.

Thus In Table 7-1:

regarding performance <u>relative to the market index</u> (columns "ISG*" and "ISG* p"):

- an instance where ISG* $p < 0.05$ and ISG* 'alpha' $\alpha_p > 0$ i.e. performance better than the market index is highlighted with shading, and

- an instance where ISG* $p < 0.05$ and ISG* 'alpha' $\alpha_p < 0$ i.e. performance worse than the market index is highlighted with a border,

regarding performance relative to ISG*'s peers (columns "peers" and "anova p"):

- an instance where anova $p < 0.05$ and ISG* 'alpha' α_p is greater than the mean of the peers' 'alpha' α_p i.e. performance better than the peers is highlighted with shading, and

- an instance where anova $p < 0.05$ and ISG* 'alpha' α_p is less than the mean of the peers' 'alpha' α_p i.e. performance worse than the peers is highlighted with a border.

This convention is adhered to and adapted as necessary in all tables that follow in this chapter.

In assessing the results in Table 7-1 attention is first focussed on the top left quadrant: market model – own benchmarks[2]. All 'alphas' α_p of ISG* and peers are generally quite small and vary little with 'time sample' (the latter partly reflects the fact that the set of peers considered remains the same in each case, as illustrated in Table 4-3 on p.46; this is not the case for every fund below). Although modestly positive statistically significant 'alphas' are found for time sample 'x4' (0.164) and 'x8' (0.392), 'alpha' α_p is not statistically significantly different from zero in the other three 'time samples' 'all', 'ind' and 'x12'. And there is no difference of interest between the 'alpha' α_p of ISG* and that of its peers.

In the bottom left quadrant of Table 7-1 ISG*'s 'alpha' α_p is significantly positive for four out of five 'time samples' which might be taken as evidence of superior performance relative to the market index. On the other hand the very large negative result for time sample 'ind' suggests that these results may not be a reliable measure of a consistent phenomenon, but are at least partly due to random sampling error or are sensitive to the period of time selected for analysis. It is fair to conclude, however, that the

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[2] But see previous footnote on p.109.

performance of ISG* differs somewhat depending on whether its own Hoare Govett smaller companies index or the broad FTSE All Share index is used.

Looking at the right hand columns in Table 7-1 it is clear that 'alpha' α_p estimates can differ considerably depending on whether the market model or the CAPM is used. Overall the CAPM results are less suggestive of any difference in mean return between ISG* and the market index, or between ISG* and its four peers.

7.2.2 ISG* Conditional Variance

Table 7-2 provides summary information regarding the variability of ISG* about the benchmark index and of its peers about the benchmark index, and whether these differ.

The layout of Table 7-2 is similar to Table 7-1 on p.109 and is explained there.

The first column of results headed "ISG*" reports the mean value of ISG*'s conditional variance as estimated by the 'best' GARCH model. The second column, "peers" reports the mean value of conditional variance across all of the peer funds. The third column, headed "Δ" gives the difference between these two: peers minus ISG* i.e. a measure of the extent, if any, to which the ethical fund has achieved lower variability than its peers. The fourth column headed "p-value" reports the result of an anova test of the hypothesis of equality of mean conditional variance between ISG* and the peers, so that positive "Δ" together with $p < 0.05$ is evidence of lower variability on the part of ISG*.

Table 7-2 ISG* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		ISG*	peers	Δ	p-value	ISG*	peers	Δ	p-value
OWN	all	2.248	3.154	0.906	0.003	2.247	3.083	0.836	0.003
	ind	2.248	2.748	0.500	0.068	2.247	2.766	0.519	0.117
	x4	2.037	2.221	0.183	0.445	1.948	2.233	0.285	0.237
	x8	1.989	2.134	0.145	0.601	2.253	2.147	-0.106	0.682
	x12	2.088	1.691	-0.398	0.040	2.100	1.783	-0.316	0.080
FTSE	all	4.324	3.154	-1.170	0.000	4.318	3.083	-1.235	0.000
	ind	8.040	2.748	-5.292	0.000	4.360	2.766	-1.594	0.000
	x4	3.882	2.221	-1.662	0.000	4.013	2.233	-1.779	0.000
	x8	4.291	2.134	-2.157	0.000	4.249	2.147	-2.102	0.000
	x12	4.494	1.691	-2.803	0.000	4.937	1.783	-3.154	0.000

There is an important difference between the 'alpha' α_p estimates of the previous section in Table 7-1 on p.109 and the mean conditional variance estimates in Table 7-2.

Consider, for example, the market-model[3] own-benchmark case with time sample 'all' (top left in both tables). The 'alpha' α_p estimate of 0.095 in Table 7-1 on p.109 is a single point estimate that is then compared with four other point estimates, one for each of the peers. The sample size of 5 necessarily limits what can be concluded from this data. On the other hand the mean conditional variance estimate of 2.248 shown in Table 7-2 is the average of 210 conditional variance values estimated for each of the 210 months in time sample 'all' using a GARCH model. And the corresponding value for the peers of 3.154 represents 4 x 210 individual monthly conditional variance estimates. Therefore the anova test comparing the mean conditional variance of ISG* with that of its four peers has a sample size of 1050 observations (rather than 5!) and so has more power (probability of correctly rejecting a false null hypothesis).

The main conclusion suggested by Table 7-2 is that if each fund is assessed relative to its own benchmark (upper portion of table), the variability of ISG* and its peers is similar. There is some evidence of change over time in that ISG*'s conditional variance is significantly less than the peers for time sample 'all' – which goes the farthest back in time – and is significantly more than the peers for time sample 'x12' which includes only the most recent 156 months (see section 4.6 on p.51 for a description of time samples). This is borne out in Figure 7-1 below.

If ISG* is assessed relative to the FTSE All Share index (as are the peers) the result is quite different – the variability of ISG* is much larger, and is convincingly greater than that of its peers. This illustrates the importance of the 'small company effect' which was particularly highlighted by previous researchers Luther et al (1992), Luther and Matatko (1994) and Gregory et al. (1997), as discussed in section 2.4.1 on p.10. The results in Table 7-2 also illustrate how making use of each fund's own nominated benchmark has accommodated the concerns of these researchers in this case.

[3] See footnote 1 on p.109.

It is also notable in Table 7-2 that, although the estimates do differ, there is a large degree of consistency between the market model results (to the left) and those of the CAPM (to the right).

A great many somewhat-similar graphs could be drawn to illustrate the results in Table 7-2. Following the discussion in section 5.2.3 on p.64 the market model is here favoured over the CAPM. Of the five time samples 'all', 'ind', 'x4', 'x8' and 'x12' time sample 'ind' provides a good compromise when comparing an individual ethical fund with its peers as it maximises the use of the available data by comparing with at least the three closest peers (see section 4.6.6 on p.58). In the case of ISG* here, time sample 'ind' contains all four peers (see Table 4-15 on p.52). Figure 7-1 therefore provides a reasonable illustration of the results.

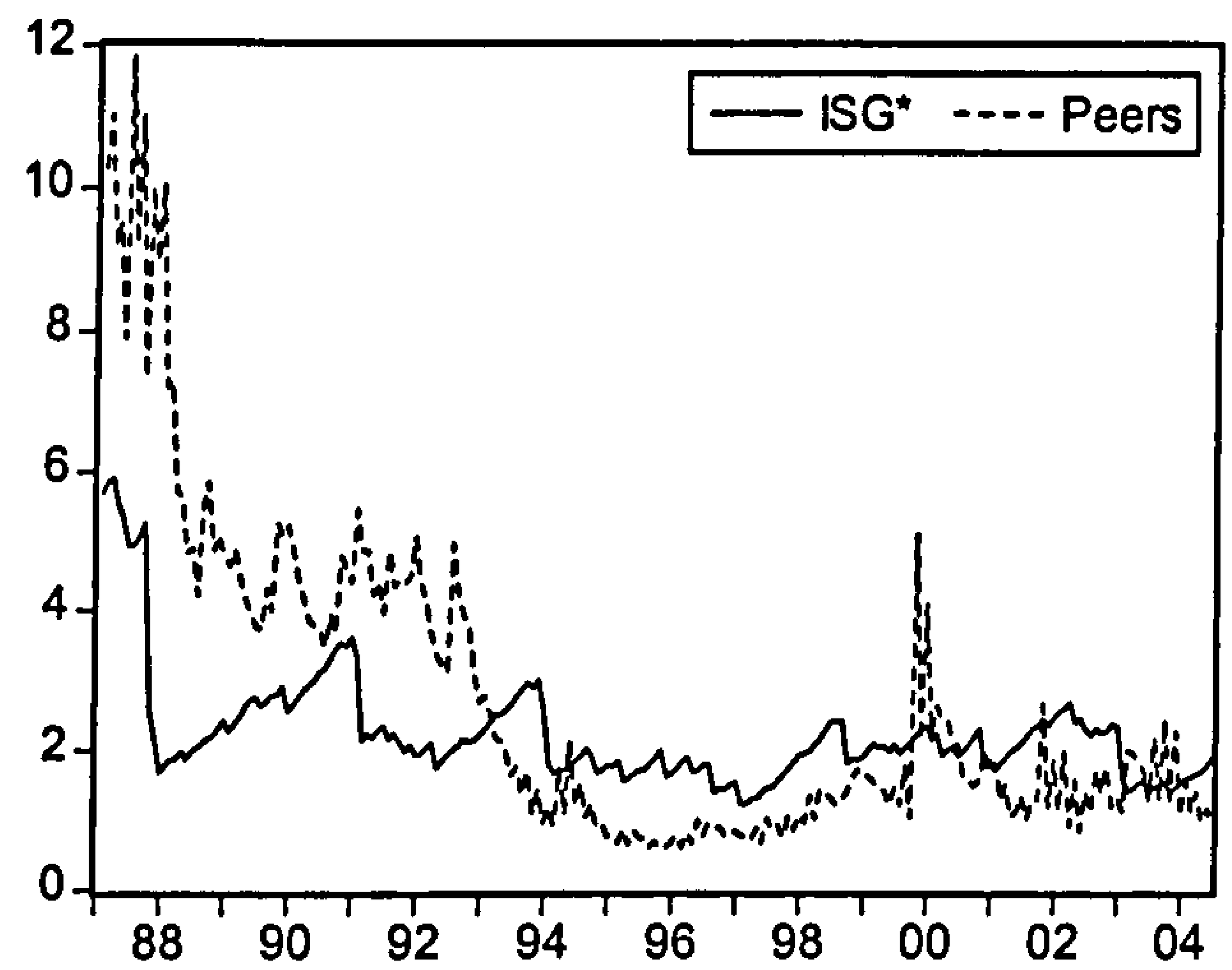


Figure 7-1 ISG* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

In Figure 7-1 the solid line shows the conditional variance of ISG* as estimated by the selected 'best' GARCH model. The broken line shows, for each monthly observation, the average of the corresponding conditional variance estimates for each of the four peers.

Pleasingly, Figure 7-1 illustrates the conclusions suggested by Table 7-2 on p.112 well. ISG*'s conditional variance is similar to the peers overall, but tends to be lower than the peers before around 1993 and greater than the peers for much of the time after this.

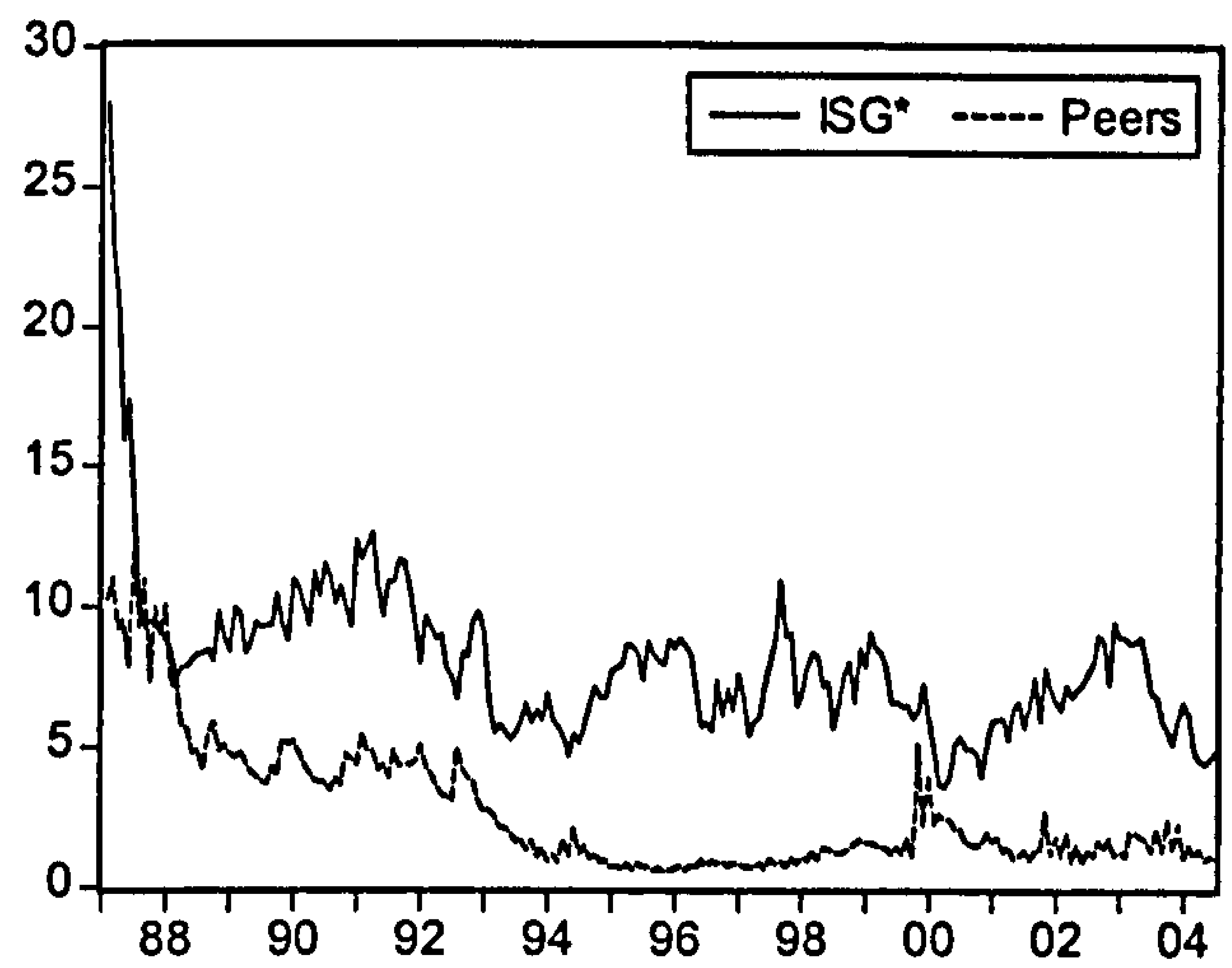


Figure 7-2 ISG* and Peers: Conditional Variance with FTSE All (market model, sample 'ind')

Figure 7-2 is similar to Figure 7-1 except that the FTSE All Share index is used as benchmark for ISG* in addition to the four peers, and this illustrates the results in the lower portion of Table 7-2 on p.112. In comparing the two Figures, note that the peer line (dashed) is identical in each figure, but the horizontal axis differs.

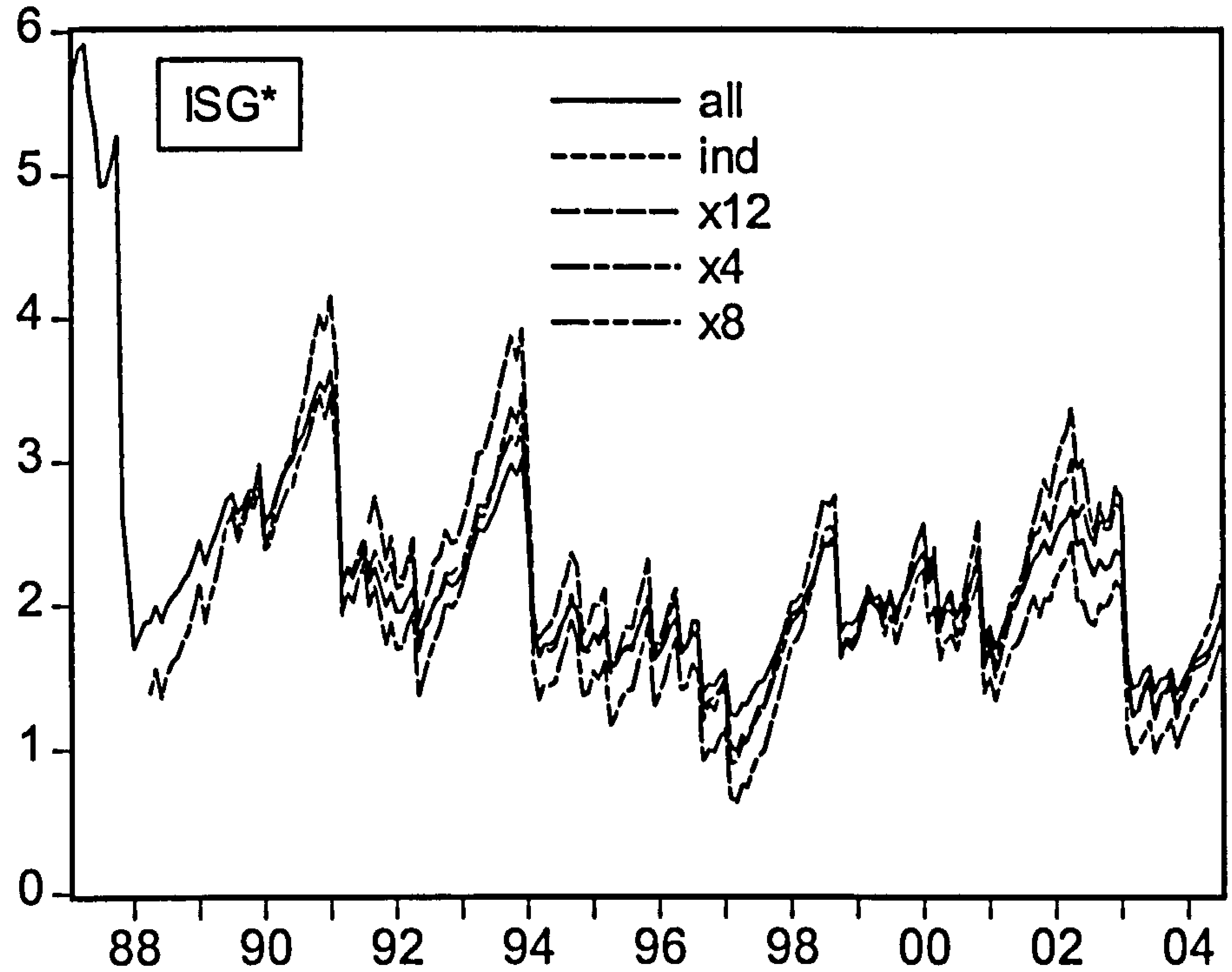
7.2.3 ISG* Agreement Between Time Samples

As an indication of the robustness of the results, it is of interest to consider the extent to which the five time samples 'all', 'ind', 'x4', 'x8' and 'x12' agree. Here this is done only for the market model – own benchmark results.

Considering the five estimated series of ethical fund ISG*'s conditional variance (consisting of between 156 and 210 observations) whose mean values are reported in Table 7-2 on p.112 (2.248, 2.248, 2.037, 1.989 and 2.088) an anova F-test of the hypothesis of equality of means rejects this null hypothesis resoundingly with p = 0.000. This provides a helpful summary of the lack of agreement apparent in Table 7-2. On the other hand, there is a considerable degree of similarity in all five of ISG*'s estimated conditional variance series in that they 'march in step': the smallest pairwise correlation coefficient between these five series is 0.808 between 'x4' and 'x8'.

Similar results are found comparing the peer's conditional variance from time sample to time sample. Equality of mean conditional variance across the five time samples is rejected with p = 0.000 and the smallest pairwise correlation coefficient between samples is 0.868 between 'all' and 'x8'.

The above is illustrated in Figure 7-3.



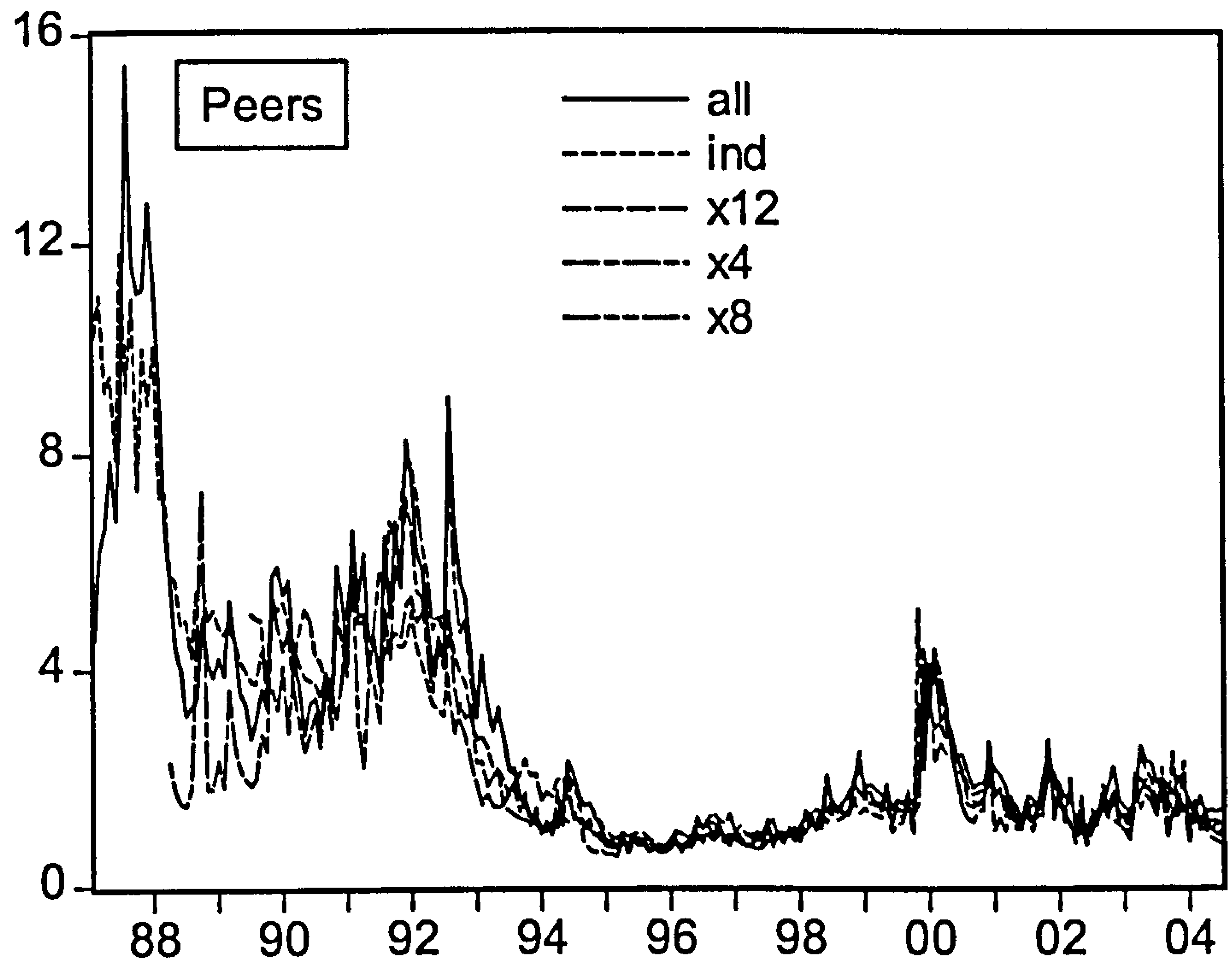


Figure 7-3 ISG* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

The left hand pane of Figure 7-3 shows the five estimated conditional variance series for ISG*, fairly highly correlated but with different mean levels. The right hand pane is similar, but for each time sample a single line shows the average of the estimated conditional variance over the four peers.

A similar comparison of mean returns using estimated 'alpha' α_p is not possible due to the difference in sample size between this and the conditional variance results (see the discussion of Table 7-2 in section 7.2.2 on p.112).

7.3 FRA* Framlington Health Results

7.3.1 FRA* Mean Returns – 'Alpha' α_p

Table 7-3 provides summary information regarding how the mean performance of FRA* compares both to the benchmark index and to its peers. Interpretation of Table 7-3 is similar to that of Table 7-1 on p.109 and is described there.

Table 7-3 FRA* and Peers: Comparing 'Alpha' α_p

		MARKET				CAPM			
		FRA*	**FRA* p**	**peers**	**anova p**	**FRA***	**FRA* p**	**peers**	**anova p**
OWN	**all**	0.628	0.060	0.174	0.454	0.538	0.095	0.163	0.510
	ind	0.816	0.018	0.334	0.347	0.624	0.040	0.217	0.541
	x4	0.338	0.398	0.476	0.734	0.286	0.465	0.347	0.912
	x8	0.642	0.152	0.401	0.638	0.597	0.178	0.353	0.679
	x12	0.257	0.591	0.259	0.995	0.221	0.639	0.194	0.946
FTSE	**all**	1.356	0.008	0.537	0.043	1.073	0.073	0.095	0.103
	ind	1.547	0.003	0.363	0.068	1.417	0.005	0.393	0.418
	x4	0.267	0.540	0.440	0.442	0.156	0.712	0.177	0.957
	x8	-9.117	0.007	0.346	0.001	1.790	0.009	0.126	0.067
	x12	0.692	0.188	-0.691	0.620	-9.714	0.002	-0.732	0.056

Focussing initially on the market model – own benchmark results[4] in the top left quadrant, there is no strong evidence of mean performance different from the benchmark index or from FRA*'s peers (see Table 4-4 on p.46 for details of these),

[4] See footnote 1 on p.109.

although in one instance, time sample 'ind', 'alpha' α_p is positive and significantly different from zero. FRA*'s 'alpha' α_p estimates are also generally similar to that of the peers and never statistically significantly different (but recall the low power of this test i.e. poor ability to reject a false null hypothesis). Comparing the CAPM results in the top right quadrant, these are very similar.

Results are also provided, in the lower left quadrant, assessing each fund against the FTSE All Share index, and on this basis there is again no strong evidence of mean performance consistently better or worse than the market index, but the results are more sensitive to the choice of time sample.

The results in Table 7-3 are provided in a consistent format for each of the dozen ethical funds. In this case, where FRA* and peers all share the same international market index, FTSE World – World, comparison with the UK domestic FTSE All Share index is less appropriate than for some other funds considered here. Given the lack of difference found between FRA* and the FTSE World – World index, results in the lower portion of Table 7-3 are more likely to reflect differences between the UK market and other international markets than to provide information about FRA* itself. This limitation of the present research is acknowledged in recommendation 5 in chapter 9 on p.193.

In summary, the evidence in Table 7-3 suggests that the mean risk-adjusted return of FRA* is not different from the FTSE World – World index or from that of its peers.

7.3.2 FRA* Conditional Variance

Table 7-4 provides summary information regarding the variability of FRA* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation of Table 7-4 is similar to Table 7-2 on p.112 and is described there.

Table 7-4 FRA* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		FRA*	peers	Δ	p-value	FRA*	peers	Δ	p-value
OWN	all	54.303	10.955	-43.348	0.000	54.230	10.957	-43.273	0.000
	ind	53.732	12.544	-41.187	0.000	59.684	12.456	-47.228	0.000
	x4	54.260	12.966	-41.294	0.000	54.231	12.910	-41.321	0.000
	x8	53.170	13.667	-39.503	0.000	53.196	13.738	-39.458	0.000
	x12	58.036	13.315	-44.721	0.000	58.101	13.475	-44.536	0.000
FTSE	all	56.261	14.882	-41.379	0.000	48.016	15.031	-32.985	0.000
	ind	59.272	17.884	-41.388	0.000	58.774	17.757	-41.016	0.000
	x4	56.485	17.537	-38.947	0.000	56.429	17.695	-38.734	0.000
	x8	51.723	19.981	-31.742	0.000	60.664	20.836	-39.827	0.000
	x12	59.315	17.091	-42.224	0.000	55.290	18.609	-36.681	0.000

Table 7-4 provides the first clear result. However it is analysed in detail, the variability of FRA* around the market index is very much greater than that of its peers.

Following the rationale used for previous ethical fund ISG* in section 7.2.2 on p.112, the results from Table 7-4 are illustrated in Figure 7-4.

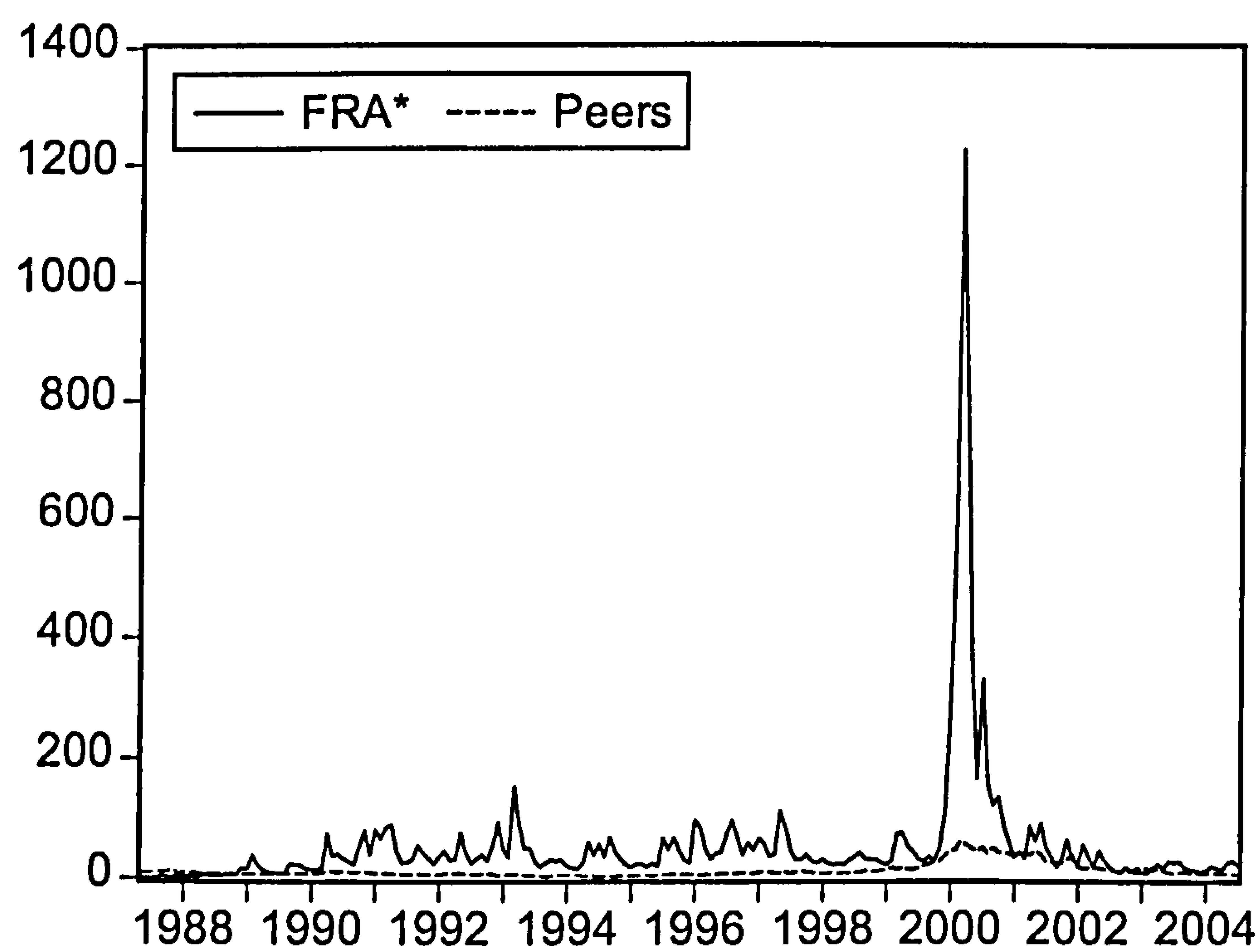


Figure 7-4 FRA* and Peers: Conditional Variance With Own Benchmarks (Market model, sample 'ind')

In Figure 7-4 it is notable that although the large conditional variance of FRA* owes a great deal to the large peak in 2000, the solid line (FRA*) is also above the dashed line (mean conditional variance of the peers) at all other times. There is no difficulty in reaching the conclusion that FRA* has much greater conditional variance than its peers.

7.3.3 FRA* Agreement Between Time Samples

Similarly to section 7.2.3 on p.115, the consistency of the FRA* conditional variance results from time sample to sample can be checked. An anova F-test for equality of means of FRA* market model – own benchmark results returns a p-value of 0.992, failing to reject the null hypothesis. This confirms the similarity evident in Table 7-4 where all market model estimates are in the 50s. The lowest pairwise correlation coefficient between time samples is 0.932 between 'all' and 'ind', again confirming a high degree of agreement.

Comparing the peers' conditional variance from time sample to time sample also fails to reject the null hypothesis of equality of means with p = 0.300, and the lowest pairwise correlation coefficient is 0.946 between 'ind' and x12.

This high degree of consistency of estimated conditional variance across time samples is illustrated in Figure 7-5 on p.122.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

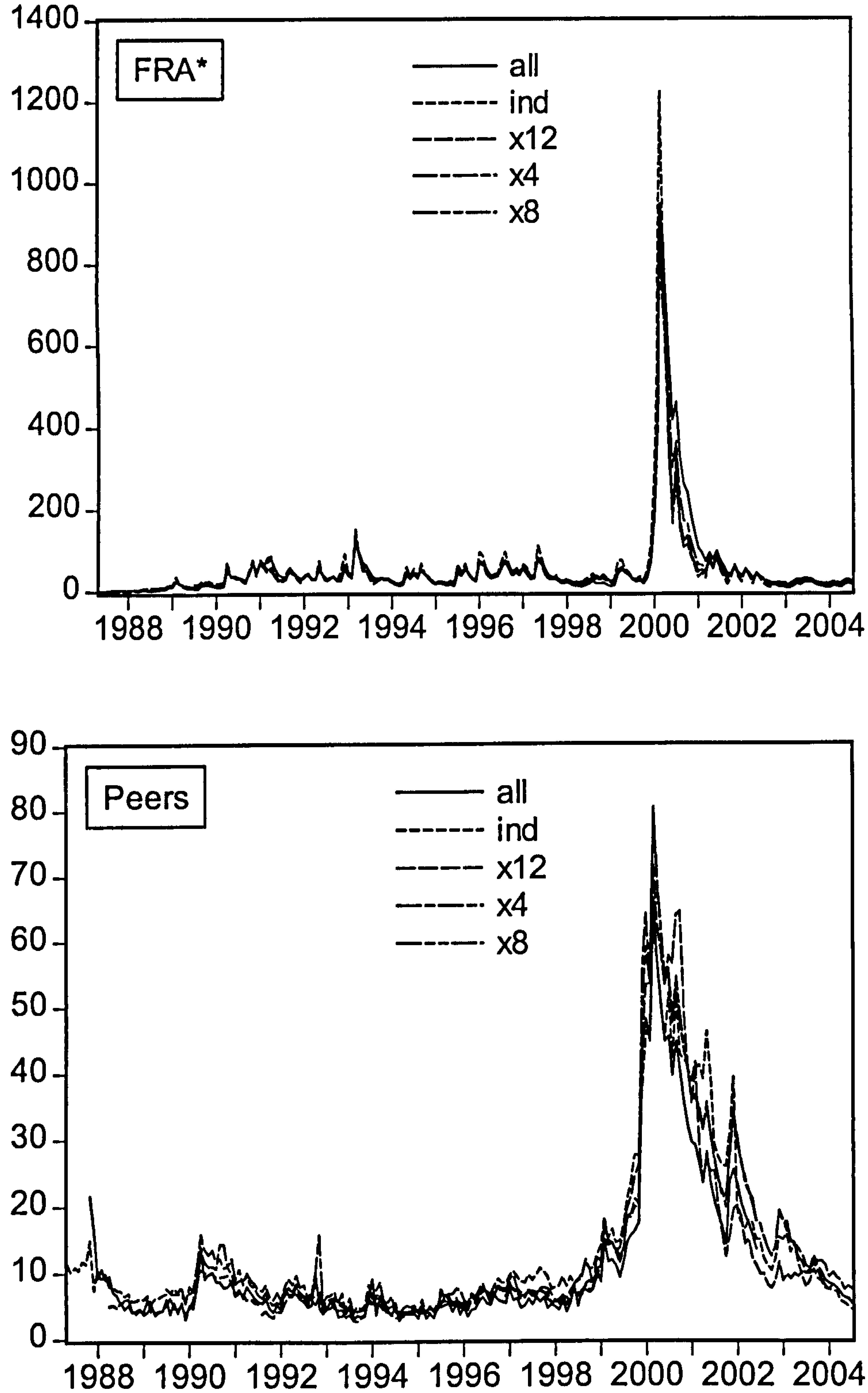


Figure 7-5 FRA* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

7.4 SWE* Scottish Widows Ethical Results

7.4.1 SWE* Mean Returns – 'Alpha' α_p

Table 7-5 provides summary information regarding how the mean performance of SWE* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-5 SWE* and Peers: Comparing 'Alpha' α_p

		MARKET				CAPM			
		SWE*	SWE* p	peers	anova p	SWE*	SWE* p	peers	anova p
OWN	all	0.061	0.066	-0.396	0.759	0.051	0.739	-0.372	0.785
	ind	0.061	0.066	0.253	0.737	0.051	0.739	0.247	0.730
	x4	0.150	0.335	-0.108	0.343	-0.023	0.881	-0.128	0.709
	x8	-3.871	0.000	-0.940	0.303	-2.915	0.000	-0.042	0.000
	x12	0.093	0.658	-1.177	0.726	0.002	0.991	-1.219	0.728
FTSE	all	-0.037	0.803	-0.732	0.682	1.913	0.000	-0.797	0.141
	ind	-0.037	0.803	-0.225	0.914	1.913	0.000	-0.297	0.288
	x4	-0.012	0.904	-0.588	0.646	0.267	0.054	-0.766	0.449
	x8	-0.098	0.413	-1.451	0.654	-0.226	0.027	-6.923	0.700
	x12	-3.231	0.001	0.005	0.001	-1.298	0.000	-1.101	0.906

Information on SWE* and its peers can be found in Table 4-5 on p.47. Similarly to ISG* in section 7.2 on p.108, SWE*'s 'own' benchmark is the Hoare Govett smaller companies index. There are up to 10 peers with a variety of 'own' benchmarks. Which peers are considered varies from time sample to time sample as illustrated in Table 4-15 on p.52.

Again, focussing on the market model – own benchmark results[5] towards the top left of Table 7-5, there is no strong evidence of a consistent difference in mean performance between SWE* and the Hoare Govett index, or between SWE* and its peers. In one time sample, 'x8', however, 'alpha' α_p is significantly large and negative indicating performance worse than the Hoare Govett index in this time sample, so that performance may be variable over time.

[5] See footnote 1 on p.109.

The conclusion of no consistent difference in mean performance follows also from assessment against the FTSE All Share index and using the CAPM instead of the market model.

7.4.2 SWE* Conditional Variance

Table 7-6 provides summary information regarding the variability of SWE* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation of Table 7-6 is similar to Table 7-2 on p.112 and is described there.

Table 7-6 SWE* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		SWE*	**peers**	**Δ**	**p-value**	**SWE***	**peers**	**Δ**	**p-value**
OWN	**all**	3.553	3.725	0.172	0.667	2.247	3.083	0.836	0.003
	ind	3.553	3.733	0.180	0.448	2.247	2.766	0.519	0.117
	x4	3.929	3.670	-0.259	0.345	1.948	2.233	0.285	0.237
	x8	7.490	4.198	-3.292	0.000	2.253	2.147	-0.106	0.682
	x12	2.918	3.826	0.909	0.111	2.100	1.783	-0.316	0.080
FTSE	**all**	5.258	7.078	7.820	0.010	5.154	7.218	2.064	0.005
	ind	5.258	9.583	4.325	0.000	5.154	9.707	4.553	0.000
	x4	5.500	8.662	3.161	0.000	4.059	8.823	4.764	0.000
	x8	5.414	9.103	3.689	0.000	5.532	10.989	5.457	0.000
	x12	12.372	8.798	-3.574	0.000	8.926	8.960	0.035	0.977

Focussing on the market model – own benchmark results towards the top left of Table 7-6 there is no strong evidence of a consistent difference in the variability of SWE* in comparison with the variability of its peers, although in one time sample, 'x8', SWE* is considerably more variable than the peers, suggesting possible instability.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-6 are illustrated in Figure 7-6, where overall similarity together with considerable variation over time is evident.

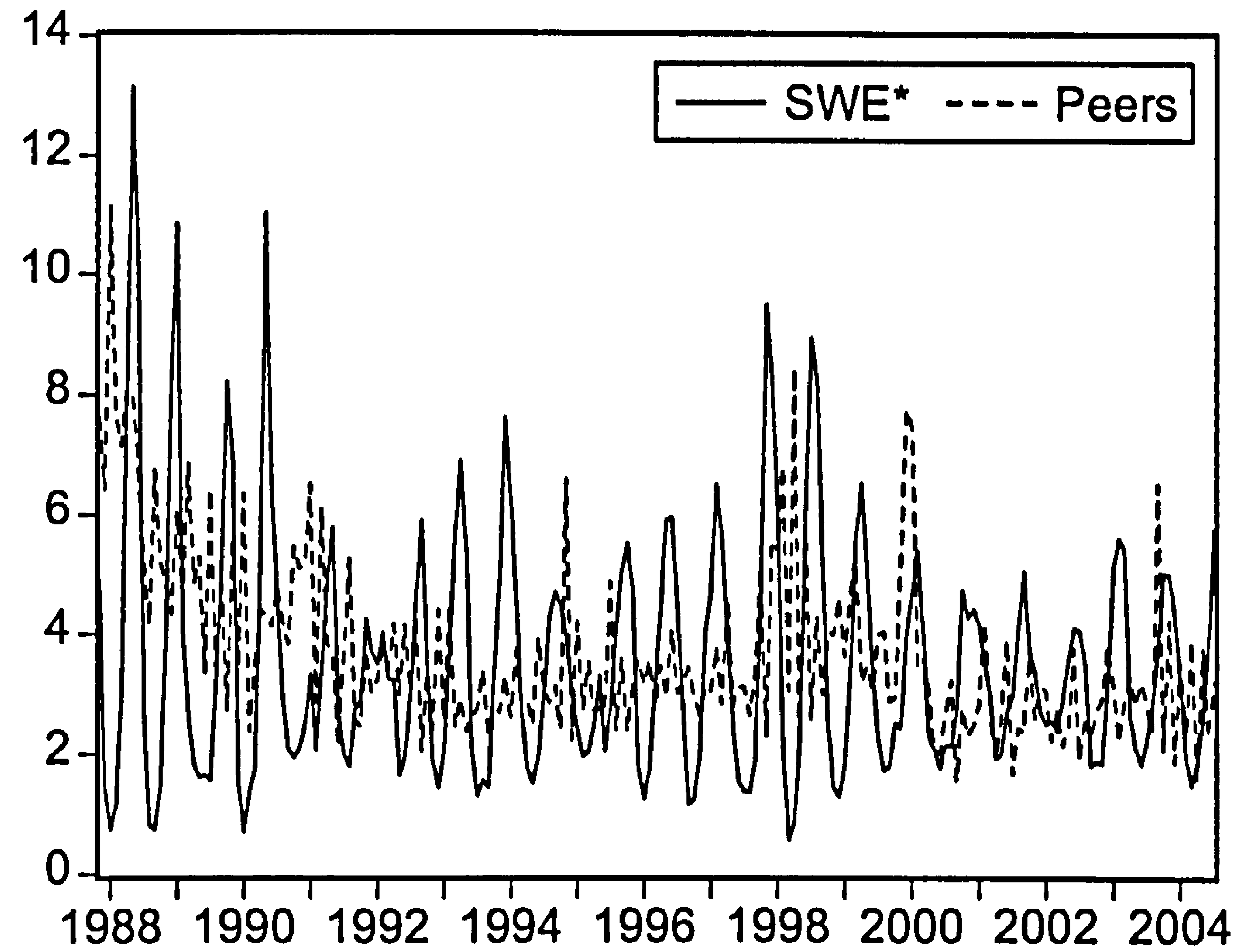


Figure 7-6 SWE* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

If, continuing with the market model, SWE* is compared not with its own Hoare Govett benchmark but with the FTSE All Share index, as in the lower quadrant of Table 7-6, its variability increases considerably. For example for time sample 'all' it increases from 3.553 to 5.258. A similar increase was observed for fund ISG* in Table 7-2 on p.112. If SWE*'s peers are also compared with the FTSE All Share index the increase in peer conditional variance is greater than that for SWE*, for example for time sample 'all' peer conditional variance increases from 3.725 to 7.078. This has the effect that when all are assessed using the FTSE All Share index, SWE* has lower variability than its peers.

Conditional variance with respect to the FTSE All Share index is illustrated in Figure 7-7.

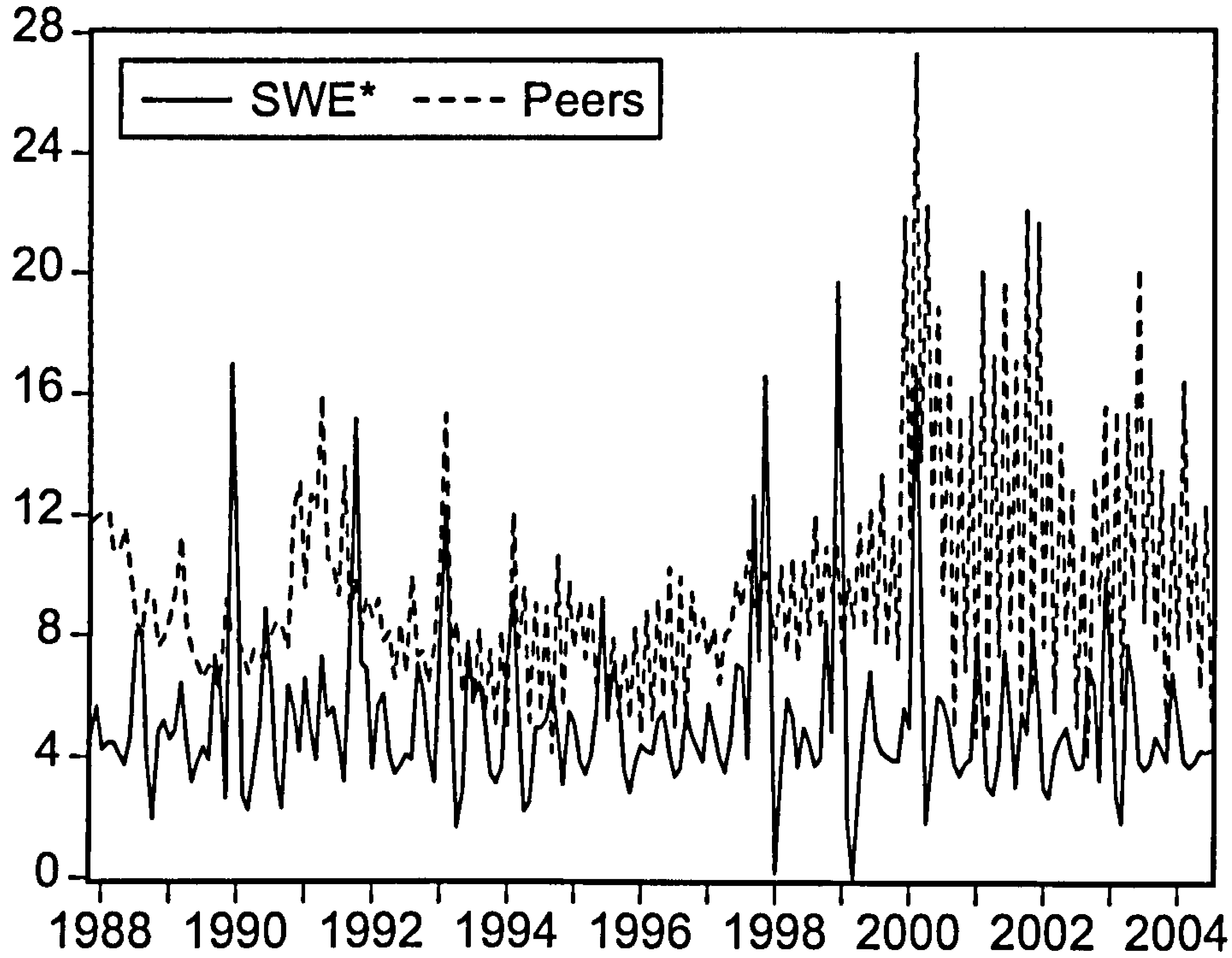


Figure 7-7 SWE* and Peers: Conditional Variance with FTSE All (market model, sample 'ind')

As shown in Table 4-15 on p.52, time sample 'ind' for SWE* includes four peers, funds MLU, SWG, SOU and BGI. Of these four peers, SWG and SOU have the FTSE All Share index as their 'own' benchmark. Therefore the large increase in mean peer conditional variance from Figure 7-6 to Figure 7-7 is due to funds MLU and BGI (whose own benchmark is the Hoare Govett index), which are more sensitive to the change of benchmark than is SWE*.

Returning to Table 7-6 on p.124, using the CAPM instead of the market model produces very similar results for SWE*, consistent with the conclusion that SWE* has similar variability to its peers if each is compared with its own benchmark, but has much lower variability than its peers if all are compared with a broad market index such the FTSE All Share index.

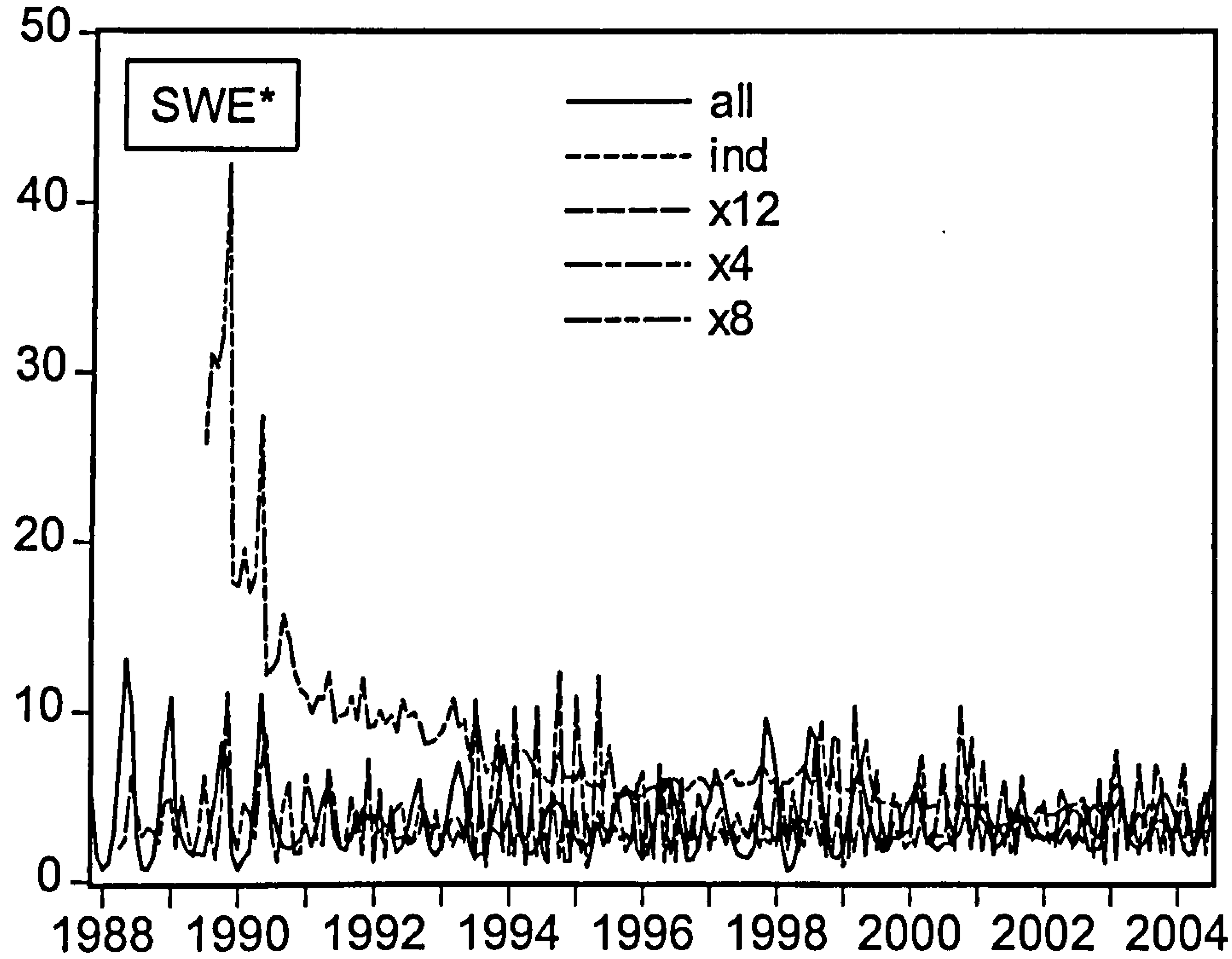
7.4.3 SWE* Agreement Between Time Samples

The consistency of the SWE* conditional variance results from time sample to time sample was checked using an anova F-test for equality of means of SWE* market model – own benchmark results. This returned a p-value of 0.000, rejecting the null hypothesis, perhaps unsurprisingly given the value of 7.490 for time sample 'x8' in comparison to the other four time samples with values of around 3 (see Table 7-6 on p.124). However, the null hypothesis is also rejected with p = 0.000 if only the other four time samples are considered. Pairwise correlation coefficients between time samples are very small (the largest being 0.114 between 'x8' and 'all' or 'ind') and even negative (-0.041 between 'x4' and 'x12' and -0.058 between 'x8' and 'x12').

From this it follows that estimates of conditional variance for SWE* are very sensitive to the dates over which this is estimated (or to random sampling error). This is likely to make it difficult to reach a general conclusion regarding its performance relative to peers.

There is greater consistency of peer conditional variance estimates from time sample to time sample, with the null hypothesis of equality of means failing to be rejected with p = 0.140. Peer pairwise correlation coefficients are quite variable but more consistent than for SWE*, ranging from +0.114 to +0.972. This is a little surprising since there is more scope for variation of peers for SWE* than for the previous two funds (SWE* has up to 10 peers whose inclusion varies from sample to sample, whereas ISG* and FRA* each have up to a maximum of four peers so that any variation between time samples is mainly due to date variation). This reinforces the conclusion regarding the sensitivity of SWE* conditional variance estimates to the period of time considered, and the difficulty of reaching general conclusions.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-8 on p.128.



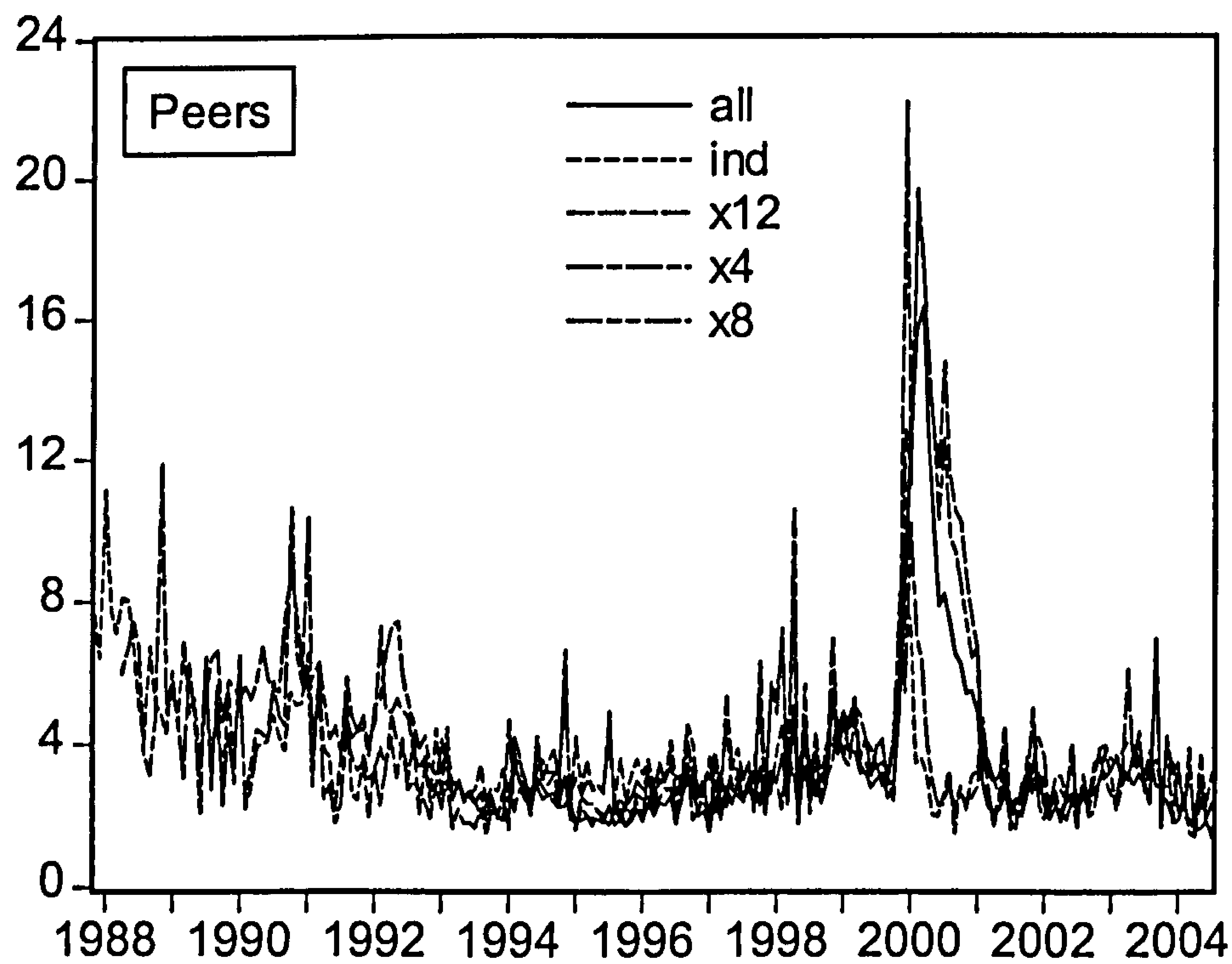


Figure 7-8 SWE* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

The left hand pane of Figure 7-8 clearly shows the high conditional variance estimate for time sample 'x8' and the low correlation between samples for ethical fund SWE*. The right hand pane, for the peers, shows the greater degree of agreement of peer conditional variance estimates. Peers differ most notably in the duration of the peak in 2000 which is smallest and briefest for 'ind' and 'x4' and longer and higher to a similar extent for the other three samples 'all', 'x8', 'x12'. These two groups of time samples differ considerably in terms of which of the up to 10 peers are included ('ind' and 'x4' contain the same four peer funds while the other time samples contain these plus additional peer funds). Therefore much of the time sample to time sample variation in peer conditional variance estimates is attributable to changes in peers considered rather than to undue sensitivity to the period of time over which they are estimated.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

7.5 FPS* Friends Provident Stewardship Income Results

7.5.1 FPS* Mean Returns – 'Alpha' α_p

Table 7-7 provides summary information regarding how the mean performance of FPS* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-7 FPS* and Peers: Comparing 'Alpha' α_p

		MARKET				CAPM			
		FPS*	**FPS* p**	**peers**	**anova p**	**FPS***	**FPS* p**	**peers**	**anova p**
OWN	**all**	0.246	0.117	-0.568	0.677	0.093	0.550	-0.004	0.614
	ind	0.476	0.001	0.086	0.140	0.323	0.010	1.593	0.599
	x8	0.712	0.000	0.504	0.855	2.333	0.001	0.459	0.118
	x12	0.433	0.004	0.353	0.908	0.319	0.032	0.305	0.981

Note: the 'own' benchmark of FPS* and all its peers is the FTSE All Share index therefore the lower part of this table would simply repeat the above.

FPS* peers are described in Table 4-6 on p.47 and their time sample membership is illustrated in Table 4-15 on p.52 where it is shown that the number of peers in each time sample varies from three ('ind') to seven ('all').

Table 7-7 offers good evidence of superior performance by FPS* relative to the market index in each time sample except 'all'.

Under the market model, FPS* 'alpha' α_p is always greater than that of its peers, suggesting superior performance. The difference is not statistically significant but in this particular instance the test is known to have low power (probability of rejecting a false null hypothesis) due to small sample size.

Under the CAPM the conclusion regarding superior performance relative to the benchmark index is unchanged but it is no longer the case that FPS* always has greater 'alpha' α_p than its peers.

7.5.2 FPS* Conditional Variance

Table 7-8 provides summary information regarding the variability of FPS* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation is similar to Table 7-2 on p.112 and is described there.

Table 7-8 FPS* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		FPS*	**peers**	**Δ**	**p-value**	**FPS***	**peers**	**Δ**	**p-value**
OWN	**all**	4.997	6.030	1.033	0.291	5.035	6.089	1.055	0.279
	ind	4.839	7.456	2.618	0.083	4.259	6.647	2.388	0.038
	x8	4.261	6.965	2.704	0.001	26.662	7.176	-19.485	0.000
	x12	4.362	7.336	2.974	0.006	3.633	7.268	3.635	0.001

Note: the 'own' benchmark of FPS* and all its peers is the FTSE All Share index therefore the lower part of this table would simply repeat the above.

Under the market model estimated mean conditional variance of FPS* is lower than that of its peers in all four time samples; this difference is statistically significantly different from zero in 'x8' and 'x12', the more recent of the time samples.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-8 are illustrated in Figure 7-9.

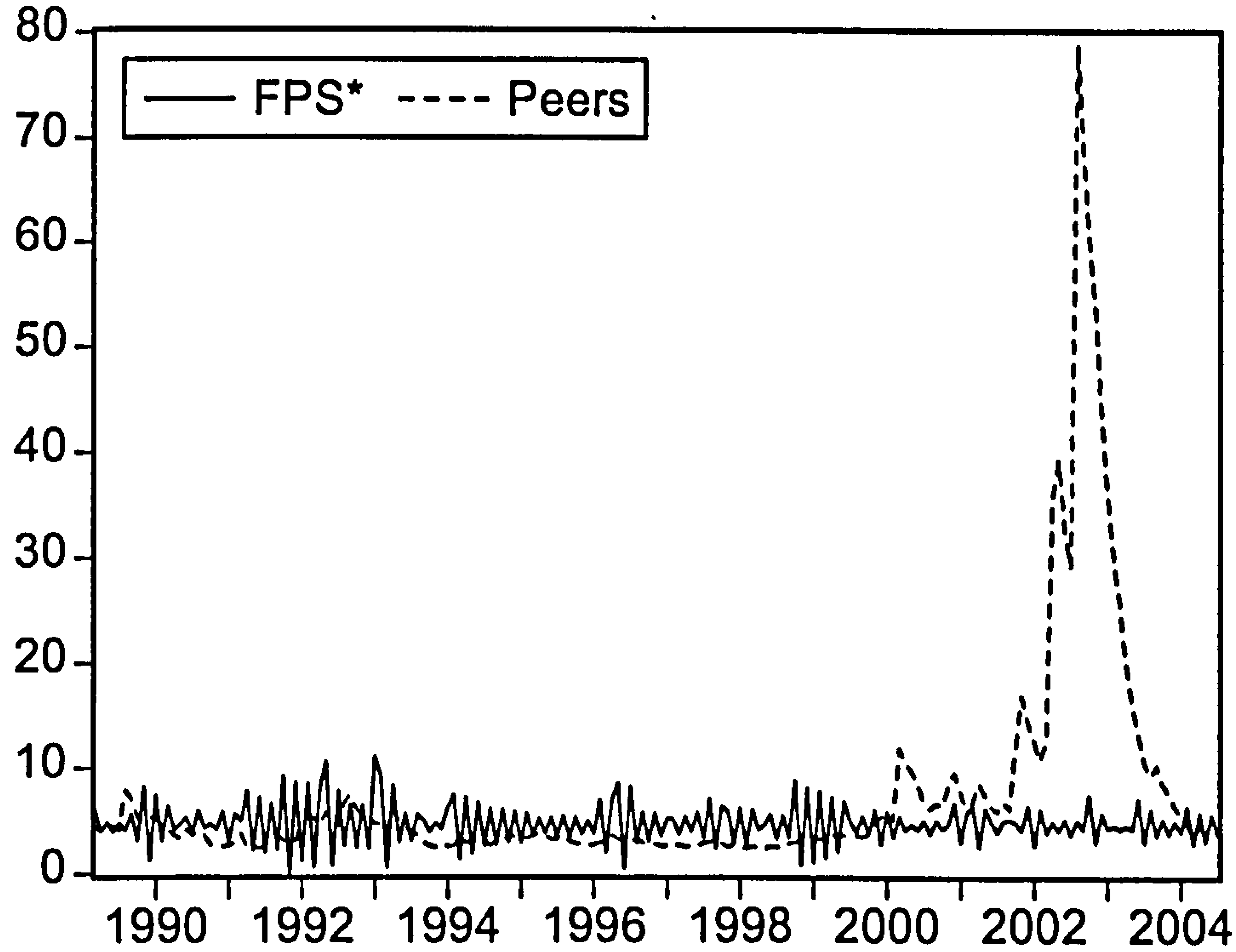


Figure 7-9 FPS* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

Figure 7-9 is interesting as it shows a large peak in the mean conditional variance of FPS*'s three closest peers from around 2002 that FPS* is unaffected by. This explains the greater statistical significance in Table 7-8 of later time samples 'x8' and 'x12'.

Were this to be a general finding, it would suggest that ethical funds might be less variable than similar conventional funds due to having more stable returns. Although Figure 7-9 shows only time sample 'ind' in the interests of conciseness, FPS*'s conditional variance is similarly flat for all four time samples.

7.5.3 FPS* Agreement Between Time Samples

The consistency of FPS* conditional variance results from time sample to sample was checked using an anova F-test for equality of means of FPS* market model – own benchmark results. This (just) failed to reject the null hypothesis of equality of means with p = 0.052. Pairwise correlation coefficients between time samples range from 0.048 between time samples 'all' and 'ind' to 0.770 between 'ind' and 'x12'. The FPS* conditional variance estimates are thus somewhat sensitive to time period considered.

FPS* has up to 7 peers whose inclusion varies from sample to sample (see Table 4-15 on p.52). There is greater variability of mean peer conditional variance estimates from time sample to time sample, with the null hypothesis of equality of means being rejected with p = 0.003. Peer pairwise correlation coefficients are reasonably high ranging from 0.557 between 'ind' and 'x8' to 0.959 between 'x8' and 'x12'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-10 on p.133.

The left hand pane of Figure 7-10 shows a general declining trend in FPS* conditional variance not apparent for time sample 'ind' in Figure 7-9.

The right hand pane of Figure 7-10 shows good agreement between the peer conditional variance estimates, differing mainly in the magnitude of the 2002 peak which is greatest for sample 'ind'. This is reasonable as 'ind' has only three peers, the fewest of the time samples so that a peak in one of these three peer funds appears to be 'diluted' as the number of peers is increased in the other time samples. On the other hand, sample 'ind' is chosen to select the three closest peers in a way that seeks to maximise the available number of observations – so it arguably gives a better picture of peer performance against which to compare FPS*.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

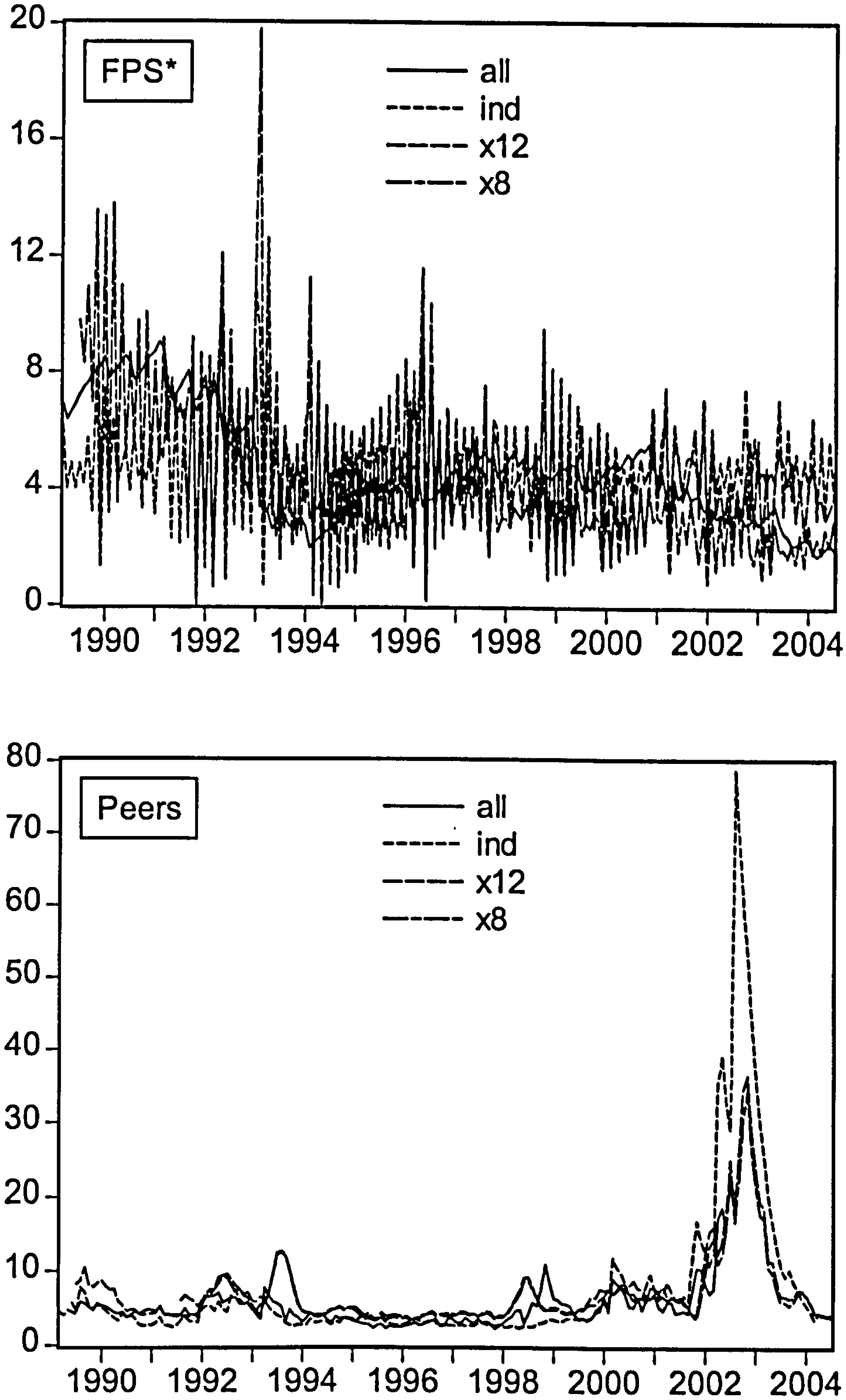


Figure 7-10 FPS* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

7.6 AAM* Allchurches Amity Results

7.6.1 AAM* Mean Returns – 'Alpha' α_p

Table 7-9 provides summary information regarding how the mean performance of AAM* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-9 AAM* and Peers: Comparing 'Alpha' α_p

		MARKET				CAPM			
		AAM*	AAM* p	peers	anova p	AAM*	AAM* p	peers	anova p
OWN	all	2.662	0.000	0.171	0.009	2.657	0.000	0.114	0.001
	ind	2.662	0.000	0.086	0.140	2.657	0.000	0.659	0.171
	x4	2.261	0.000	-0.140	0.133	2.706	0.000	0.266	0.029
	x8	1.641	0.000	0.120	0.040	-0.089	0.440	-0.463	0.693
	x12	2.034	0.000	0.195	0.149	0.243	0.114	0.171	0.950

Note: the 'own' benchmark of AAM* and all its peers is the FTSE All Share index therefore the lower part of this table would simply repeat the above.

The results in Table 7-9 are quite remarkable, indicating performance superior to the market index in every time sample under the market model. Performance is also superior to the peers for four out of five time samples and this is statistically significant in two instances, 'all' and 'x8' (recall that statistically significant results are not expected to be found often in using this test).

The CAPM results are less consistent but similar.

7.6.2 AAM* Conditional Variance

Table 7-10 provides summary information regarding the variability of AAM* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation is similar to Table 7-2 on p.112 and is described there.

Table 7-10 AAM* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		AAM*	peers	Δ	p-value	AAM*	peers	Δ	p-value
OWN	all	2.217	4.199	1.982	0.000	2.246	4.018	1.773	0.000
	ind	2.217	4.113	1.897	0.000	2.246	4.378	2.132	0.000
	x4	2.311	5.224	2.913	0.000	2.249	4.704	2.455	0.000
	x8	2.580	4.924	2.344	0.014	2.434	4.774	2.340	0.000
	x12	2.565	3.456	0.891	0.025	2.370	3.543	1.172	0.001

Note: the 'own' benchmark of AAM* and all its peers is the FTSE All Share index therefore the lower part of this table would simply repeat the above.

Results in Table 7-10 are again quite remarkable. In every time sample under both the market model and the CAPM, AAM* is less variable than its peers. This is despite the fact that for AAM* the particular peers considered varies considerably from time sample to time sample: 'ind' has three peers while 'all' has 13 (see Table 4-15 on p.52).

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-10 are illustrated in Figure 7-11.

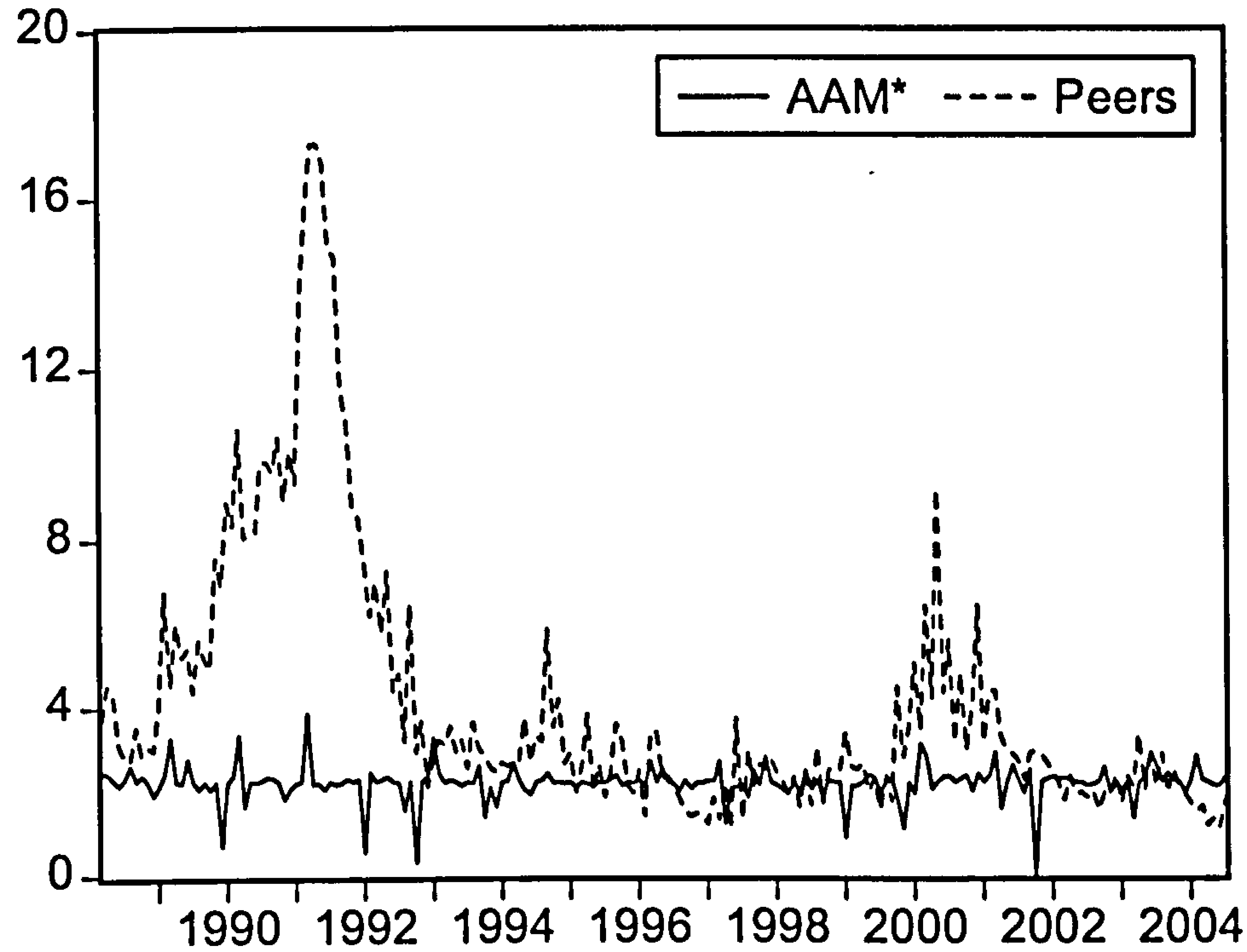


Figure 7-11 AAM* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

Figure 7-11 exhibits steady, stable variability for ethical fund AAM* during periods when that of the peers peaks considerably. This is similar to Figure 7-9 above on p.131 for ethical fund FPS*, where it was noted that this would be a pleasing result for proponents of ethical investment if it were found to be of a general nature.

7.6.3 AAM* Agreement Between Time Samples

The consistency of the AAM* conditional variance results from time sample to sample was checked using an anova F-test for equality of means of AAM* market model – own benchmark results. The null hypothesis of equality of means is rejected with $p = 0.000$

despite the fact that the range of mean conditional variance estimates shown in Table 7-10 on p.134 is quite small, from 2.217 to 2.580. This is partly a reflection of the low variance around these mean values, so that the F-test is quite discriminating. Pairwise correlation coefficients between time samples are very variable and even negative, ranging from -0.224 between 'x4' and 'x12' to 0.975 between 'all' and 'x4'. Thus, although AAM* conditional variance estimates exhibit very good consistency from time sample to time sample relative to the peers, the detailed evolution of estimated conditional variance is sensitive to the time period over which analysis is undertaken.

AAM* has up to 13 peers whose inclusion varies from sample to sample (see Table 4-15 on p.52). Equality of means is rejected with p = 0.000, and pairwise correlation coefficients range from 0.064 between 'x4' and 'x8' to 0.671 between 'all' and 'ind'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-12.

The left hand pane of Figure 7-12 conveys a visual impression of overall similarity grouped around a mean level of, say, 2.5, that is perhaps not easily captured by anova F-tests or correlation coefficients, helping to explain the consistency of results found in Table 7-10 on p.134.

With the exception of time sample 'x8' the right hand pane of Figure 7-12, the conditional variance estimates for AAM* appear somewhat grouped, although it is clear that there is much movement in some series that is not matched in others, as reflected in the correlation coefficients above. A repeat of the anova F-test for equality of mean peer conditional variance excluding time sample 'x8' also rejects the null hypothesis with p = 0.000.

This is a good, robust result – despite lots of 'noise' due to details of selection of dates and peers, AAM* is always half as variable as the peers (roughly put!).

Overall, this might be interpreted as a robust favourable result for the performance of AAM*. Despite many differences of detail as the period of time and the set of peers is varied, the variability of AAM* is simply much less than that of its peers.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

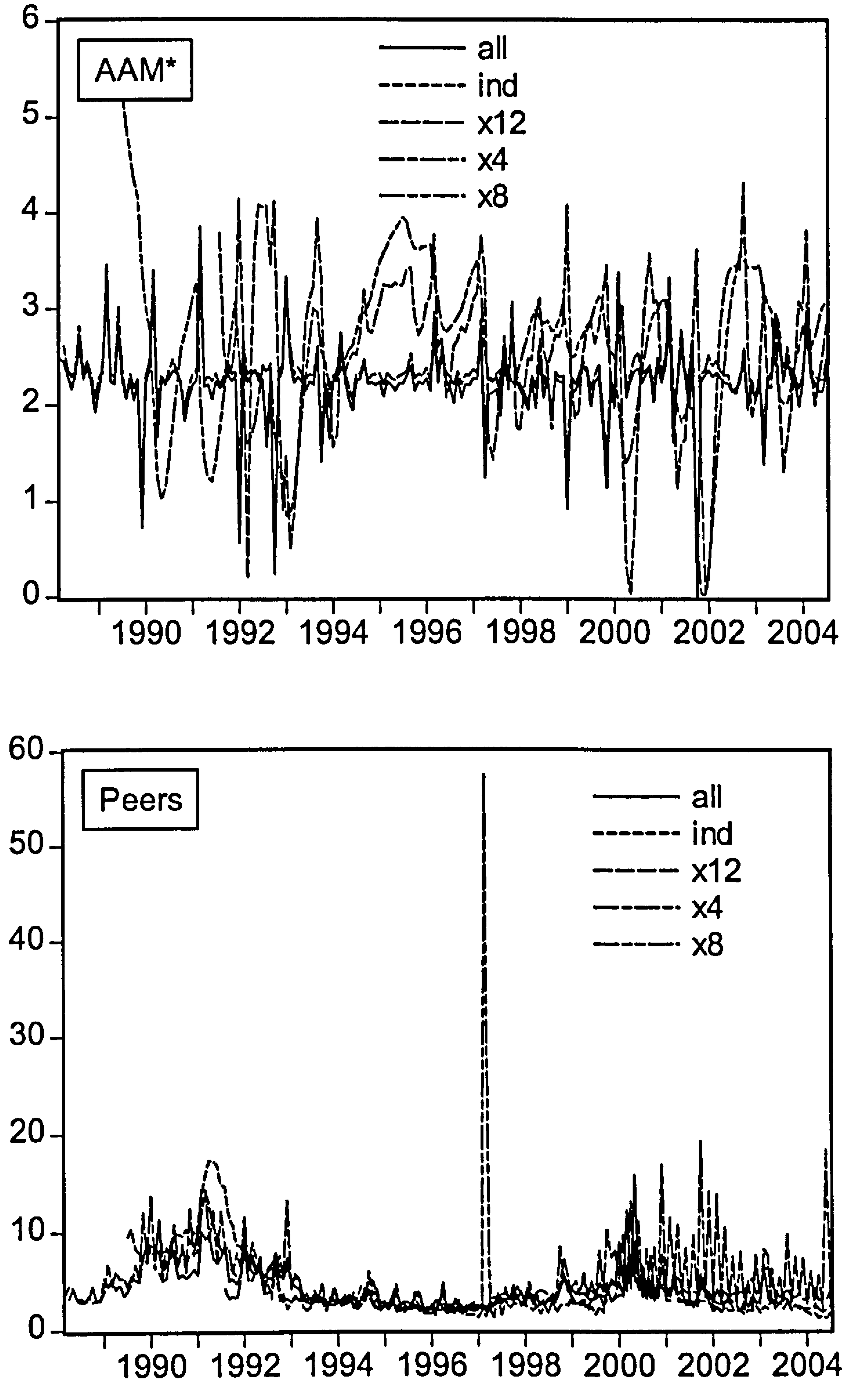


Figure 7-12 AAM* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

7.7 JUP* Jupiter Ecology Fund Results

7.7.1 JUP* Mean Returns – 'Alpha' α_p

Table 7-11 on p.138 provides summary information regarding how the mean performance of JUP* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Focussing initially on the own benchmark – market model results[6] towards the top left of Table 7-11 on p.138, JUP* exhibits highly statistically significant performance superior to the market index for the first three time samples. In time sample 'x12' – the most recent – 'alpha' α_p is positive but much smaller and not statistically significantly different from zero.

Table 7-11 JUP* and Peers: Comparing Alpha

		MARKET				CAPM			
		JUP*	**JUP* p**	**peers**	**anova p**	**JUP***	**JUP* p**	**peers**	**anova p**
OWN	**all**	2.520	0.000	0.396	0.040	0.155	0.464	0.119	0.878
	ind	2.543	0.000	0.217	0.019	0.176	0.431	0.139	0.913
	x8	2.447	0.000	-0.079	0.030	2.461	0.000	-0.310	0.054
	x12	0.365	0.086	-0.212	0.698	2.610	0.000	-0.260	0.110
FTSE	**all**	0.138	0.511	0.062	0.636	-0.045	0.823	-0.015	0.856
	ind	0.107	0.621	-0.070	0.822	-0.060	0.775	-0.616	0.832
	x8	-0.070	0.776	-0.234	0.625	-0.146	0.441	-0.693	0.791
	x12	0.175	0.455	0.053	0.721	0.143	0.479	-0.060	0.277

In comparison with the peers JUP* has statistically significantly superior performance in the form of greater estimated 'alpha' α_p in all four time samples. This difference is statistically significant at the 5% level in three of these four instances, despite the fact that with a sample size of only a few point estimates (e.g. time sample 'all' consists of six 'alpha' α_p estimates, one for JUP* and five peers; see Table 4-15 on p.52) the power of this test (probability of correctly rejecting a false null hypothesis) is relatively small.

Results under the CAPM (top right quadrant in Table 7-11) are quite different (particularly with respect to the peers), underlining the importance of the choice of

[6] See footnote 1 on p.109.

equilibrium model discussed in section 5.2.3 on p.64. The distinctive performance of JUP* found here using the market model is interesting as JUP* also has distinctive investment objectives (see section 4.4.6 p.41) but if the CAPM is used no distinctive financial performance is evident. While the two models may be considered as alternatives when considering variability of returns, the CAPM is more appropriate when focussing on mean returns, as it allows for the possibility of lending and borrowing at a risk-free rate. Therefore on balance we must conclude that JUP* does not have distinctive mean performance.

JUP*'s investment objective is "to invest worldwide" (see section 4.4.6 on p.41) and JUP* and its peers have the FTSE World index as their benchmark (see Table 4-8 on p.48). Therefore it is not surprising that the results in the lower portion of Table 7-11, estimated using the FTSE All Share index throughout instead of the funds' 'own' benchmarks, are quite different. To compare mainly UK-focussed funds having different benchmarks to a common broad index would be a useful exercise, but for JUP* these results are of limited relevance, and are included mainly in the interests of consistency of reporting from fund to fund. This is a weakness in the present research noted in recommendation 5 in chapter 9 on p.193.

7.7.2 JUP* Conditional Variance

Table 7-12 provides summary information regarding the variability of JUP* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation is similar to Table 7-2 on p.112 and is described there.

Table 7-12 JUP* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		JUP*	peers	Δ	p-value	JUP*	peers	Δ	p-value
OWN	all	13.356	4.685	-8.670	0.000	10.745	4.653	-6.092	0.000
	ind	12.427	4.370	-8.057	0.000	11.188	4.473	-6.715	0.000
	x8	13.304	3.870	-9.434	0.000	12.410	4.138	-8.271	0.000
	x12	11.793	6.316	-5.477	0.000	12.479	6.188	-6.291	0.000
FTSE	all	11.015	7.056	-3.959	0.000	11.033	7.054	-3.979	0.000
	ind	11.412	11.779	0.368	0.624	11.419	8.244	-3.175	0.000
	x8	10.417	7.258	-3.159	0.000	11.238	7.721	-3.516	0.000
	x12	11.717	4.673	-7.044	0.000	11.486	4.813	-6.673	0.000

Results in Table 7-12 are very consistent – JUP* is much more variable than its peers, with an estimated mean conditional variance at times 2 or 3 times as large. It makes little difference which equilibrium return model is used, or which benchmark index is used. This is despite the fact noted at the end of the previous section that the FTSE All Share index is not very relevant in this case – JUP* returns are simply very variable.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-12 are illustrated in Figure 7-13.

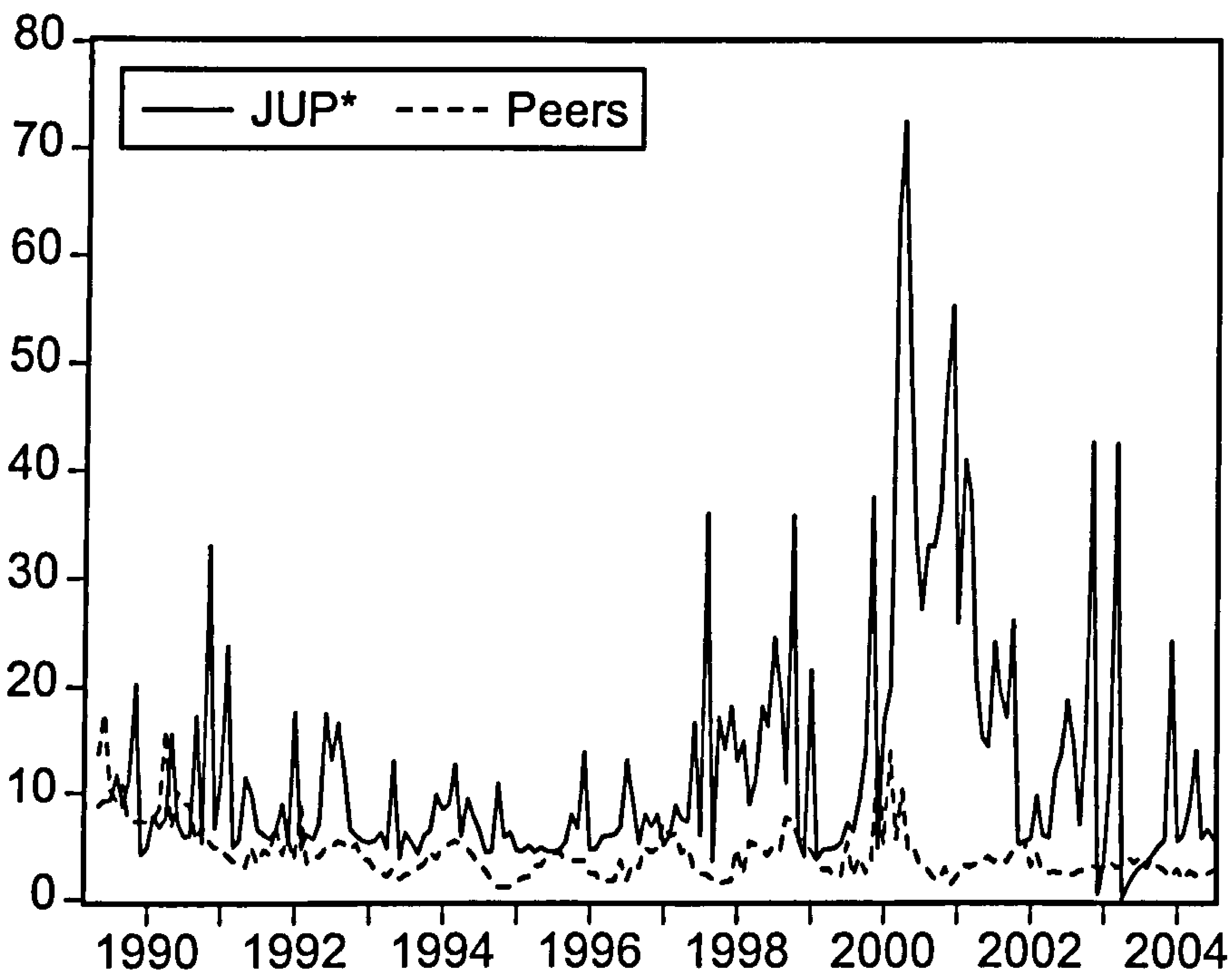


Figure 7-13 JUP* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

In Figure 7-13 there is a peak in JUP* conditional variance from around 2000 but this is not the source of the pronounced difference between JUP* and its peers as JUP* is also above the peers in almost every other time period.

7.7.3 JUP* Agreement Between Time Samples

The consistency of the JUP* conditional variance results from time sample to sample was checked using an anova F-test for equality of means of JUP* market model – own benchmark results. The null hypothesis of equality of means is not rejected with $p = 0.488$. Pairwise correlation coefficients are also consistently reasonably large, ranging from 0.751 between 'x8' and 'x12' to 0.998 between 'ind' and 'x8'.

Results for the peers are more variable from time sample to time sample and equality of means is rejected with $p = 0.000$ and pairwise correlation coefficients ranging from 0.620 between 'all' and 'x8' to 0.853 between 'ind' and 'x8'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-14.

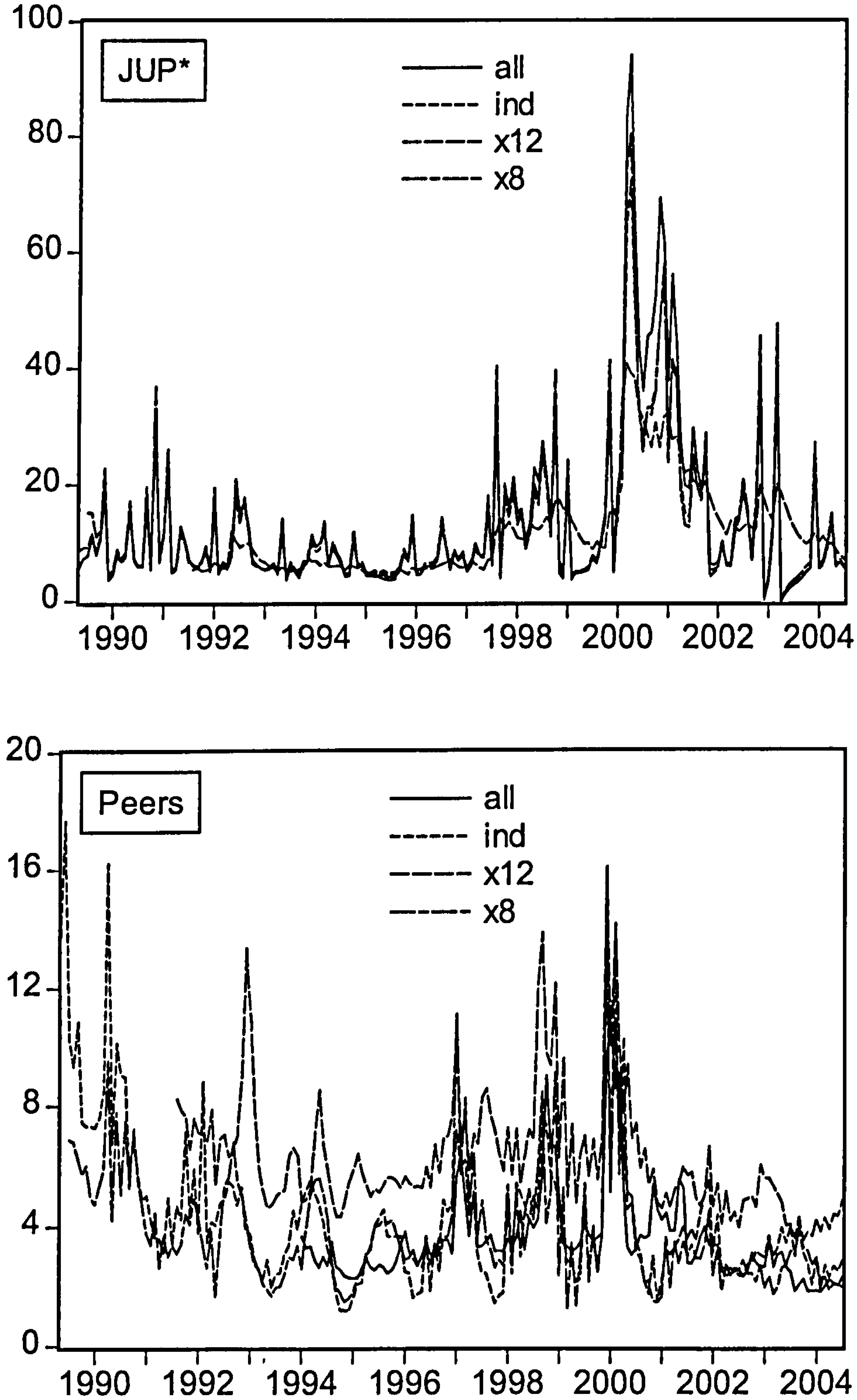


Figure 7-14 JUP* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

The greater consistency of JUP* results (left hand pane) than peer results (right hand pane) can be seen in Figure 7-14.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

7.8 CFE* City Financial Ethical (Acorn) Results

7.8.1 CFE* Mean Returns – 'Alpha' α_p

Table 7-13 provides summary information regarding how the mean performance of CFE* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-13 CFE* and Peers: Comparing Alpha

		MARKET				CAPM			
		CFE*	**CFE* p**	**peers**	**anova p**	**CFE***	**CFE* p**	**peers**	**anova p**
OWN	**all**	0.318	0.227	-1.223	0.631	0.061	0.791	-0.920	0.679
	ind	0.374	0.144	0.322	0.868	0.010	0.970	0.233	0.476
	x8	0.352	0.185	0.371	0.955	0.062	0.792	0.274	0.879
	x12	0.320	0.167	0.209	0.478	-0.085	0.146	0.154	0.757
FTSE	**all**	-0.119	0.267	-0.009	0.786	-0.341	0.025	0.114	0.475
	ind	-0.131	0.488	0.509	0.237	-0.298	0.160	0.249	0.412
	x8	0.099	0.000	0.030	0.800	0.462	0.180	-0.125	0.123
	x12	-0.074	0.754	-0.332	0.702	-0.213	0.203	-0.457	0.744

Table 7-13 provides good evidence that the mean risk-adjusted performance of CFE* does not differ from that of the market index or from that of its peers, whichever method of analysis is employed.

7.8.2 CFE* Conditional Variance

Table 7-14 provides summary information regarding the variability of CFE* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation is similar to Table 7-2 on p.112 and is described there.

Table 7-14 CFE* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		CFE*	peers	Δ	p-value	CFE*	peers	Δ	p-value
OWN	all	12.346	16.749	4.403	0.004	11.218	15.696	4.478	0.000
	ind	12.317	5.917	-6.400	0.000	11.710	5.957	-5.753	0.000
	x8	12.509	5.874	-6.635	0.000	11.616	9.676	-1.940	0.003
	x12	11.165	7.990	-3.174	0.000	8.938	8.398	-0.540	0.544
FTSE	all	12.040	9.028	-3.012	0.000	13.373	8.927	-4.446	0.000
	ind	12.719	7.365	-5.354	0.000	11.041	7.639	-3.402	0.000
	x8	10.718	7.347	-3.371	0.000	12.089	7.077	-5.012	0.000
	x12	9.525	7.563	-1.961	0.002	9.006	8.533	-0.473	0.674

In Table 7-14 CFE* is generally more variable than its peers and this difference is generally statistically significant. Although (see Table 4-9 on p.48) all have international benchmarks, using the FTSE All Share index makes little difference.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-14 are illustrated in Figure 7-15.

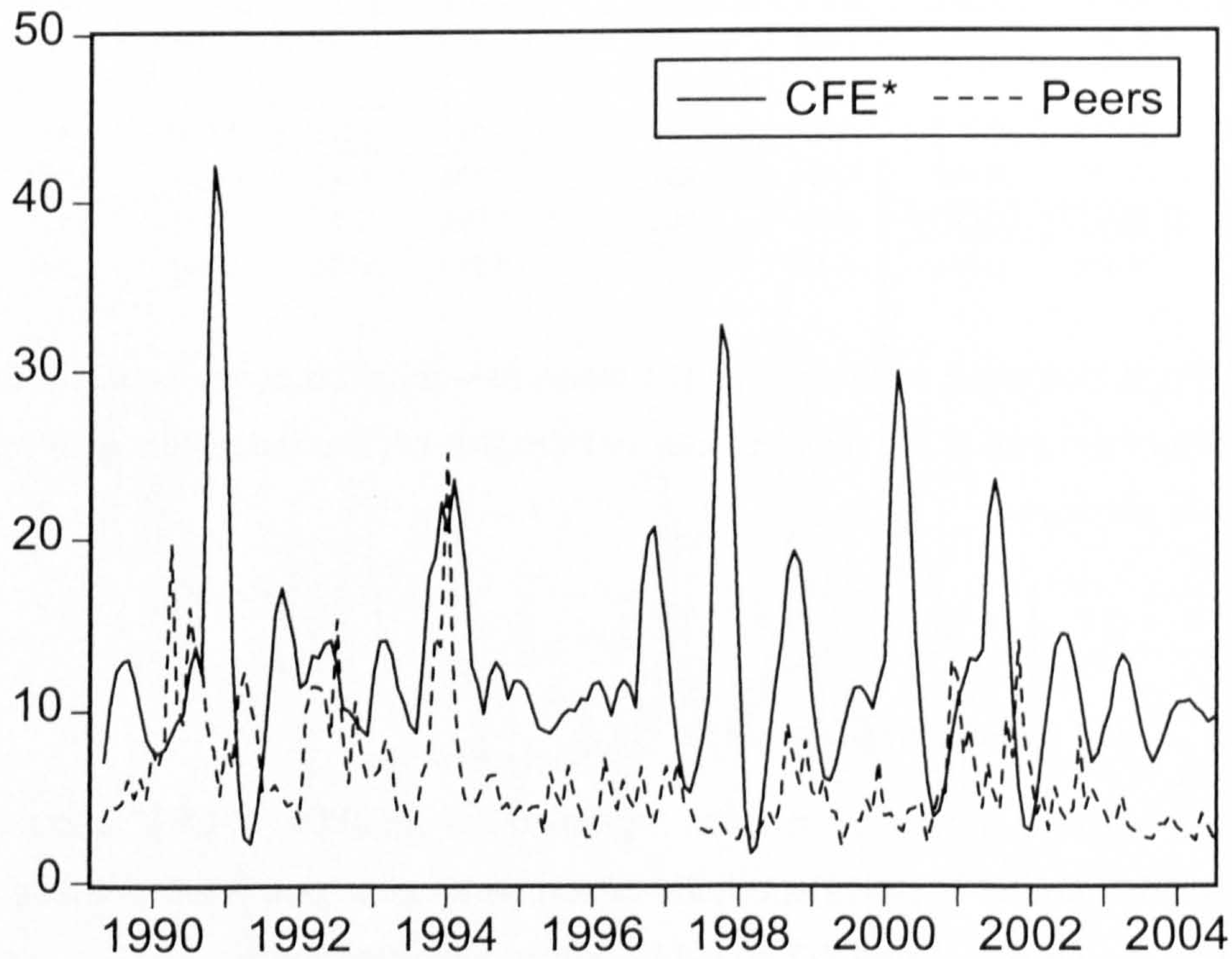


Figure 7-15 CFE* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

In Figure 7-15 the difference in variability between CFE* and its peers can be seen to persist throughout the time period considered.

7.8.3 CFE* Agreement Between Time Samples

The consistency of the CFE* conditional variance results from time sample to sample was checked using an anova F-test for equality of means of CFE* market model – own benchmark results. The null hypothesis of equality of means is not rejected with $p = 0.206$, in line with the closely grouped estimates from 11.165 to 12.509 shown in Table 7-14 on p.144. Pairwise correlation coefficients are high, the lowest being 0.928 between 'all' and 'x12'.

Unsurprisingly, for the peers equality of means from time sample to time sample is rejected with $p = 0.000$. This is unsurprising due to the very large mean estimate of 16.749 shown in Table 7-14 on p.144. Pairwise correlation coefficients range from 0.620 between 'all' and 'x8' to 0.853 between 'ind' and 'x8'. Pairwise correlation coefficients amongst the peers are also variable, from 0.031 between 'all' and 'x8' to 0.974 between 'ind' and 'x8'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-16 on p.146.

In Figure 7-16 the consistency of CFE* conditional variance estimates is clearly apparent in the left hand pane, with the more variable peer results shown in the right hand pane. The quite different peer results for time sample 'all' in Table 7-14 on p.144 appear also in Figure 7-16 where this series is almost above the other three, and diverges further from around 1995.

Ethical fund CFE* has only four peers therefore the set of peers with which it is compared varies little from time sample to time sample. Therefore the variation in peer conditional variance results reflect a sensitivity to the time period analysed that is not evident in CFE* itself.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

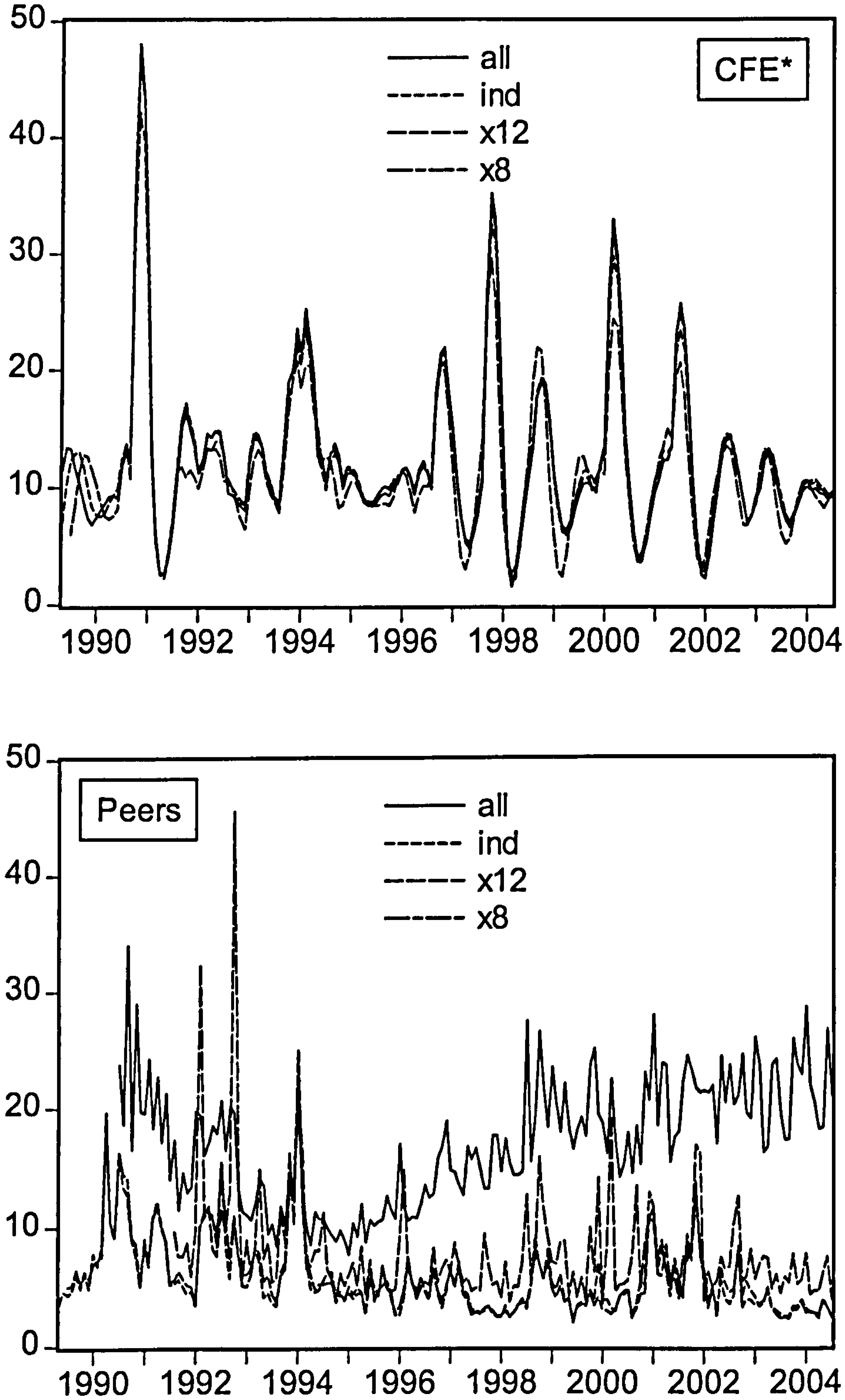


Figure 7-16 CFE* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

7.9 AEG* Aegon Ethical Results

7.9.1 AEG* Mean Returns – 'Alpha' α_p

Table 7-15 provides summary information regarding how the mean performance of AEG* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-15 AEG* and Peers: Comparing Alpha

		MARKET				CAPM			
		AEG*	AEG* p	peers	anova p	AEG*	AEG* p	peers	anova p
OWN	all	-5.521	0.000	-0.127	0.001	-0.059	0.720	-0.280	0.857
	ind	-5.521	0.000	0.243	0.000	-0.059	0.720	0.022	0.723
	x12	0.174	0.000	-0.039	0.755	0.106	0.000	-0.115	0.755
FTSE	all	-5.521	0.000	-0.142	0.001	-0.059	0.720	-0.281	0.856
	ind	-5.521	0.000	0.063	0.000	-0.059	0.720	0.017	0.693
	x12	0.174	0.000	0.054	0.769	0.106	0.000	-0.018	0.776

Information on AEG* and its peers can be found in Table 4-10 on p.48, where it can be seen that AEG* and all but three of its up to 15 peers have the FTSE All Share index as benchmark, which explains the high degree of similarity between the upper and lower portions of Table 7-15.

The results in Table 7-15 are very mixed and provide no strong evidence of over- or under-performance by AEG* relative to the market index or to its peers. It is odd to see highly statistically significant results in both directions as opposed to, say, a lack of statistically significant results, and this suggests that the 'alpha' α_p estimates are somewhat unstable.

Membership of the peers in each of the three time samples is shown in Table 4-15 on p.52. There it can be seen that all three time samples have 11 peer funds in common. Therefore the instability of the estimates is due to sensitivity to the time period analysed and not due to changes in peers from time sample to time sample.

7.9.2 AEG* Conditional Variance

Table 7-16 provides summary information regarding the variability of AEG* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation is similar to Table 7-2 on p.112 and is described there.

Table 7-16 AEG* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		AEG*	peers	Δ	p-value	AEG*	peers	Δ	p-value
OWN	all	5.084	4.222	-0.862	0.058	4.530	4.110	-0.419	0.245
	ind	5.084	3.234	-1.760	0.000	4.530	3.271	-1.259	0.000
	x12	6.988	4.596	-2.392	0.000	6.825	4.631	-2.194	0.000
FTSE	all	5.084	3.921	-1.163	0.012	4.530	3.821	-0.709	0.058
	ind	5.084	2.899	-2.185	0.000	4.530	2.875	-1.655	0.000
	x12	6.988	3.627	-3.361	0.000	6.825	3.646	-3.179	0.000

In Table 7-16 the estimated variability of AEG* is always greater than that of its peers, and this difference is statistically different from zero in most cases.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-16 are illustrated in Figure 7-17.

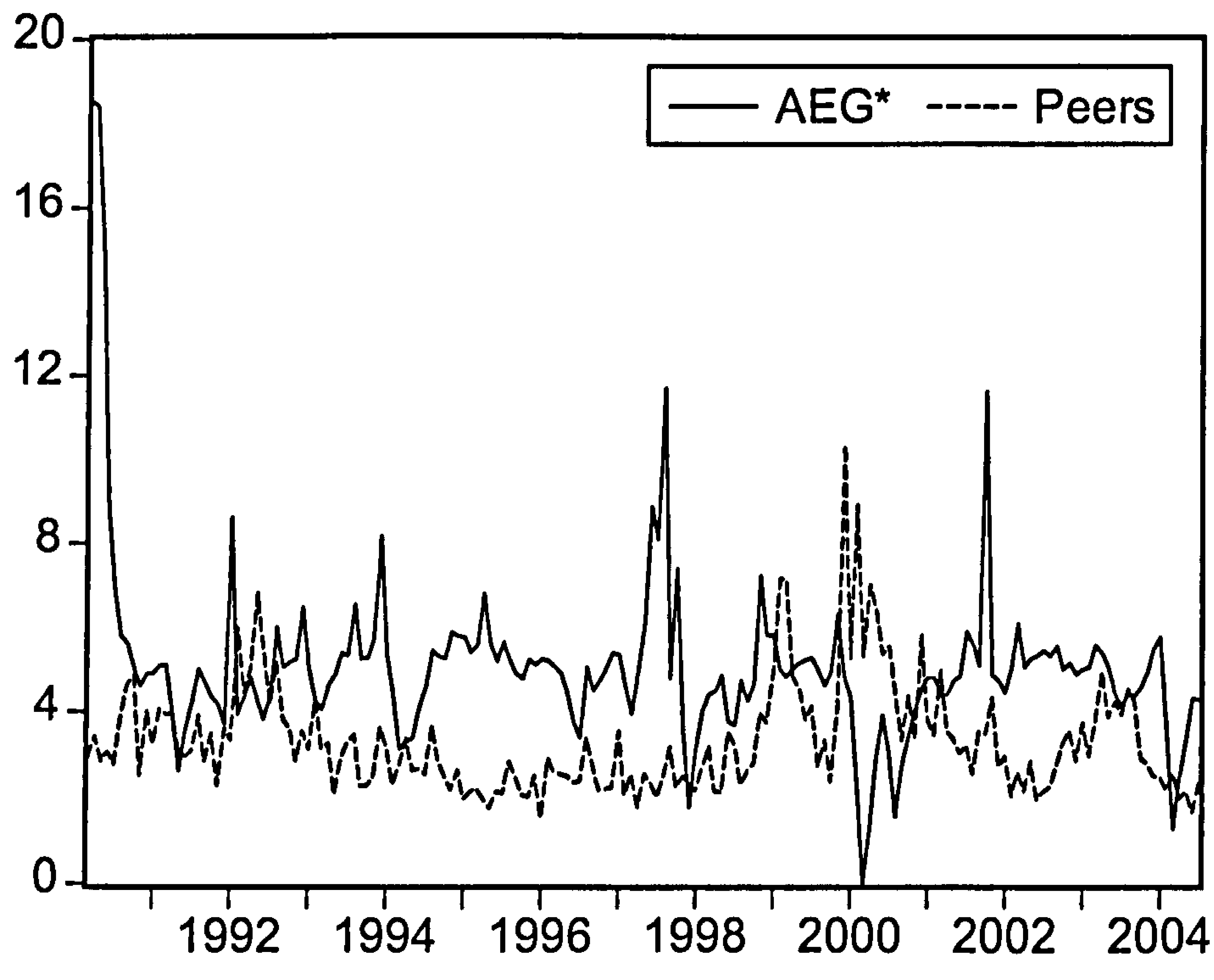


Figure 7-17 AEG* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

In Figure 7-17 the conditional variance of AEG* is almost always greater than that of its peers although the two diverge greatly in 2000 when that of AEG* falls and that of the peers peaks.

7.9.3 AEG* Agreement Between Time Samples

There are effectively two AEG* time samples: 'all'/'ind' with mean conditional variance of 5.084 and 'x12' with 6.998 (market model – own benchmark results). Unsurprisingly an anova F-test for equality of means rejects the null hypothesis of equality of means with $p = 0.000$. The correlation coefficient of -0.018 between these is almost zero.

For the peers the three time samples do return different estimates due to changes in peer membership, and equality of means from time sample to time sample is rejected with $p = 0.000$. Again this is unsurprising given the range of values from 3.234 to 4.596 in Table 7-16 on p.148. The peer results are reasonably highly correlated, the lowest pairwise correlation coefficient being 0.699 between 'all' and 'ind'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-18 on p.150.

The very different two conditional variance estimates ('all'/'ind' being effectively the same here) for AEG* can be seen in the left pane of Figure 7-18, while the peers in the right pane illustrate the greater agreement indicated by the F-test and correlation coefficients.

Clearly, in the case of ethical fund AEG* estimated conditional variance, as well as 'alpha' α_p, is very sensitive to the time period selected for analysis.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

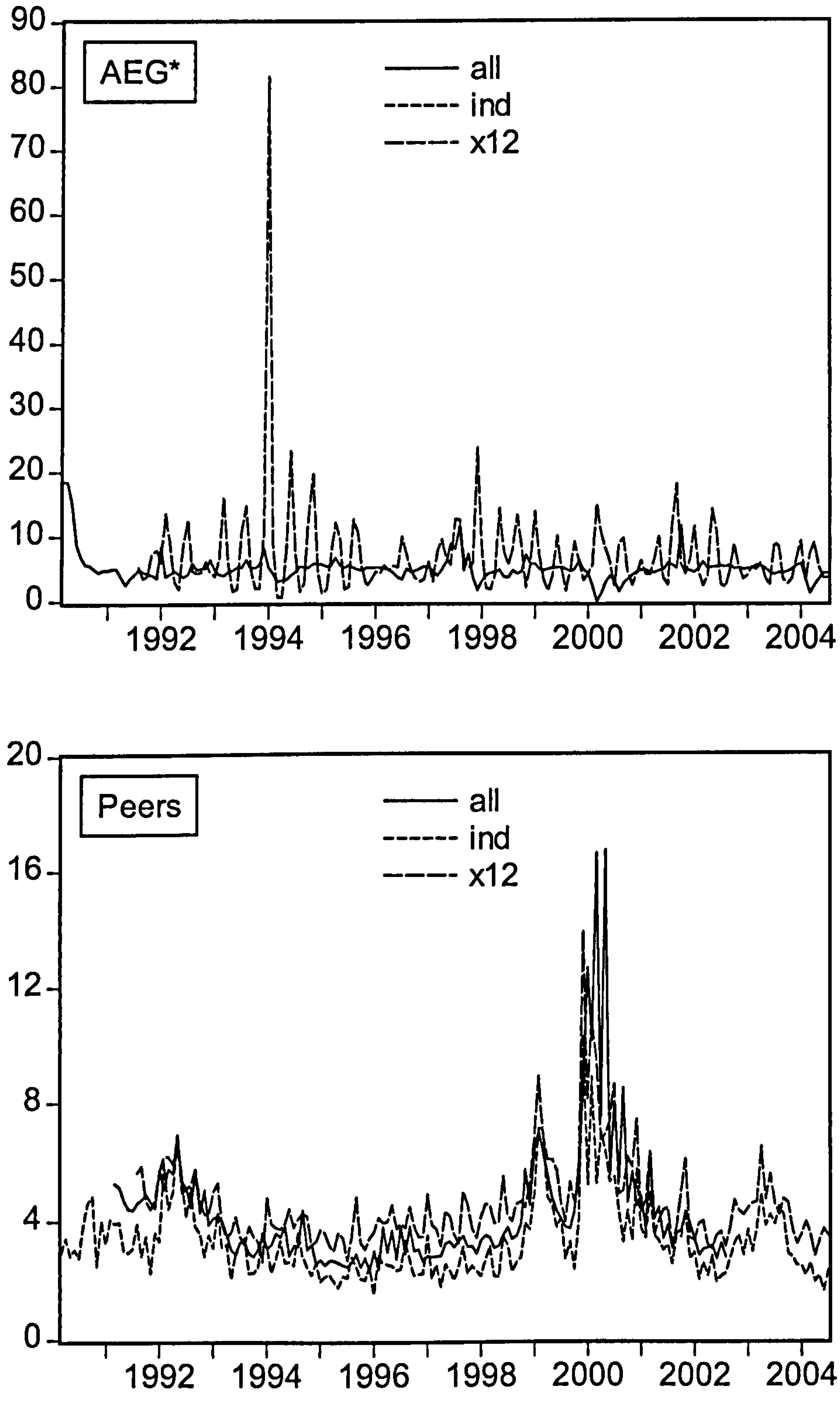


Figure 7-18 AEG* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

7.10 SET* Sovereign Ethical Results

7.10.1 SET* Mean Returns – 'Alpha' α_p

Table 7-17 provides summary information regarding how the mean performance of SET* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-17 SET* and Peers: Comparing Alpha

		MARKET				CAPM			
		SET*	**SET* p**	**peers**	**anova p**	**SET***	**SET* p**	**peers**	**anova p**
OWN	**all**	-0.140	0.493	-0.045	0.940	-0.336	0.037	-0.108	0.847
	ind	-0.140	0.493	-0.453	0.880	-0.336	0.037	-0.335	0.999
	x8	-0.140	0.493	-0.453	0.880	-0.336	0.037	-0.335	0.999
	x12	-0.198	0.257	0.060	0.817	-0.168	0.261	0.015	0.866
FTSE	**all**	-0.140	0.493	-0.064	0.952	-0.336	0.037	-0.116	0.853
	ind	-0.140	0.493	-0.453	0.880	-0.336	0.037	-0.335	0.999
	x8	-0.140	0.493	-0.453	0.880	-0.336	0.037	-0.335	0.999
	x12	-0.198	0.257	0.188	0.689	-0.168	0.261	0.145	0.735

Information on SET* and its peers can be found in Table 4-11 on p.49 where it can be seen that all but one (CUO) of SET*'s up to 15 peers has the FTSE All Share index as its 'own' benchmark. Peer CUO is a member of only time samples 'all' and 'x12' (see Table 4-15 on p.52) which explains why only these numbers in the "peers" columns vary between the upper and lower portions of Table 7-17. Similar comments apply to Table 7-18 below

Under the CAPM, Table 7-17 presents evidence of SET* performance worse than the market index but no different from its peers.

7.10.2 SET* Conditional Variance

Table 7-16 provides summary information regarding the variability of SET* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation is similar to Table 7-2 on p.112 and is described there.

Table 7-18 SET* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		SET*	peers	Δ	p-value	SET*	peers	Δ	p-value
OWN	all	7.941	4.583	-3.358	0.000	8.161	4.504	-3.656	0.000
	ind	7.941	4.290	-3.651	0.000	8.161	4.145	-4.016	0.000
	x8	7.941	4.290	-3.651	0.000	8.161	4.145	-4.016	0.000
	x12	9.073	4.546	-4.527	0.000	9.572	4.633	-4.939	0.000
FTSE	all	7.941	4.401	-3.540	0.000	8.161	4.330	-3.830	0.000
	ind	7.941	4.290	-3.651	0.000	8.161	4.145	-4.016	0.000
	x8	7.941	4.290	-3.651	0.000	8.161	4.145	-4.016	0.000
	x12	9.073	3.865	-5.207	0.000	9.572	3.939	-5.633	0.000

It is clear from Table 7-16 that the returns of SET* are very much more variable than those of its peers, with mean conditional variance around twice as large.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-16 are illustrated in Figure 7-19.

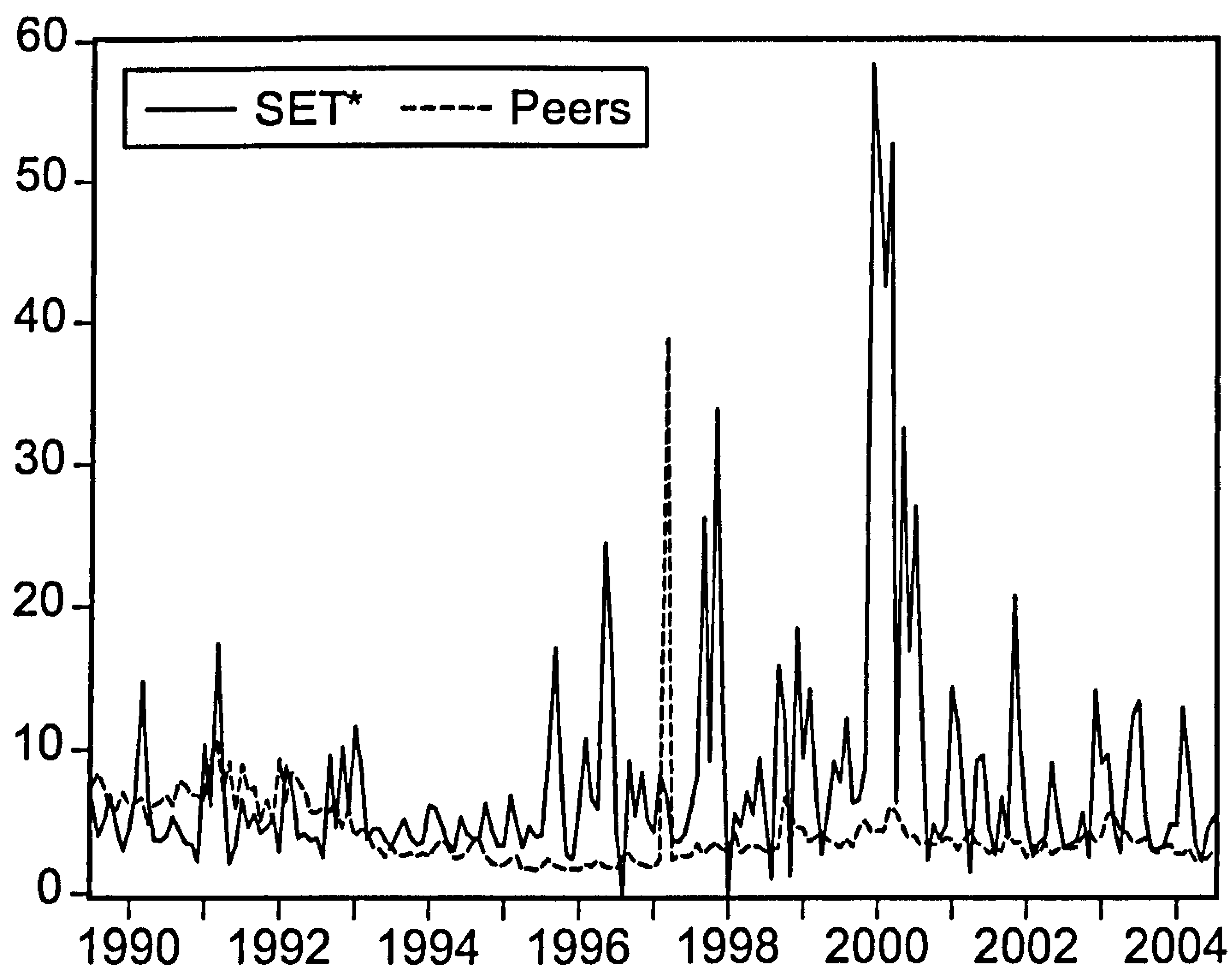


Figure 7-19 SET* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

In Figure 7-19, although the conditional variance of the peers peaks very considerably in early 1997, SET* has a still greater peak around 2000 and in addition is above the peers in most time periods.

7.10.3 SET* Agreement Between Time Samples

Similarly to AEG* above in section 7.9.3 on p.149 above. SET* is effectively estimated over two time samples: 'all'/'ind'/'x8' and 'x12', with quite different mean conditional variance of 7.941 and 9.073, respectively. It is therefore somewhat surprising that the usual F-test fails to reject the null hypothesis of equality of these means with $p = 0.516$ – this result is due to the very large variation about these mean values. The correlation between the two conditional variance estimates is 0.555.

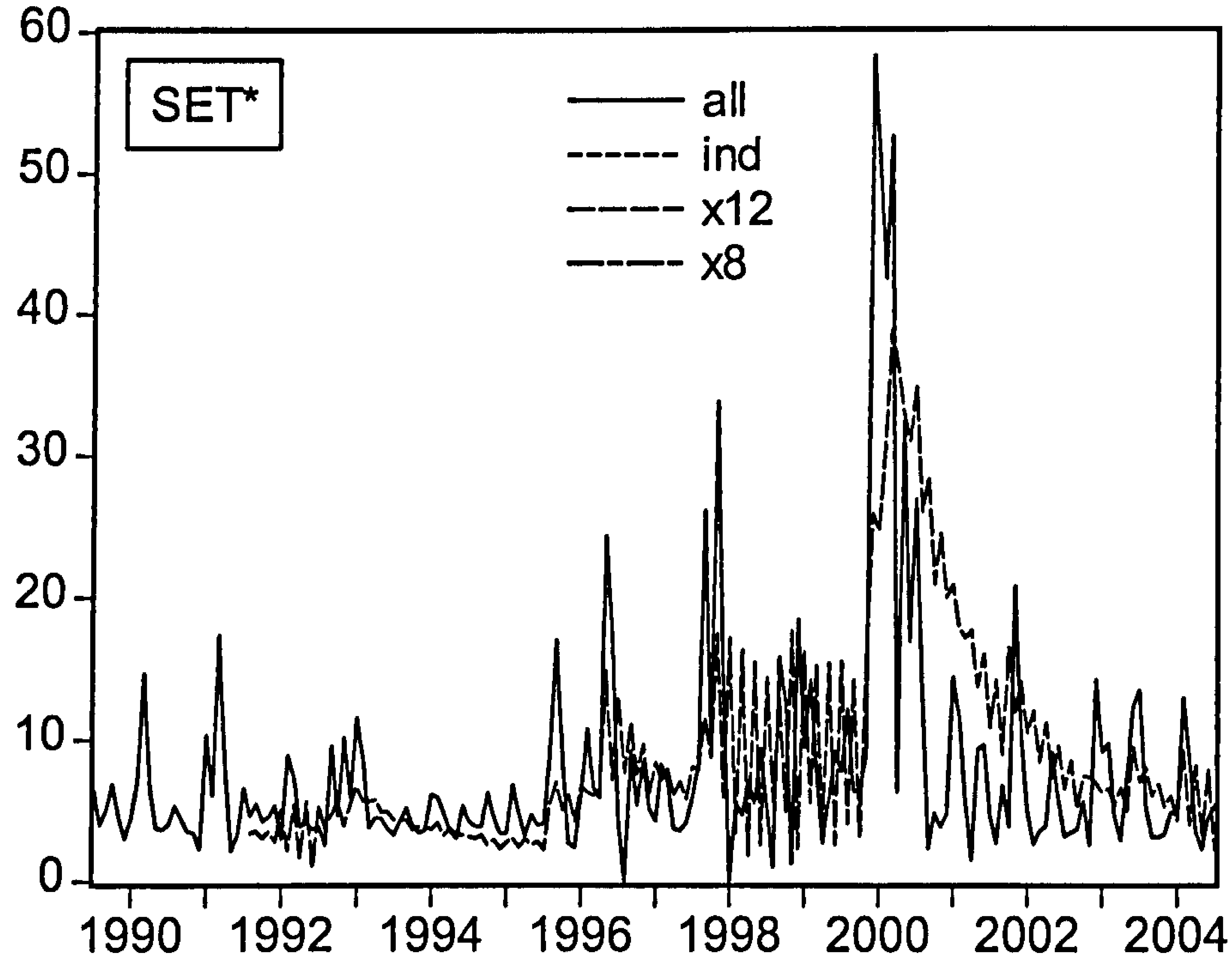
For the peers there are effectively three time samples: 'all', 'ind'/'x8' and ''x12', and equality of mean conditional variance across time samples also fails to be rejected with $p = 0.732$. The pairwise correlation coefficients vary considerably from 0.268 between 'all' and 'ind'/'x8' to 0.702 between 'all' and 'x12'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-20 on p.154.

In the left hand pane of Figure 7-20 the wide variance of the two SET* conditional variance estimates ('all'/'ind'/'x8' and 'x12') is apparent, helping to explain why the F-test above failed to find a statistically significant difference between two seemingly very different mean values.

In the right hand pane of Figure 7-20 the closer agreement of peer estimates is apparent, with the exception of the large single-month peak in 'ind'/'x8' in 1997. Despite this peak, time sample 'ind'/'x8' has the lowest mean value of the three, being less than the other two estimates in most months.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.



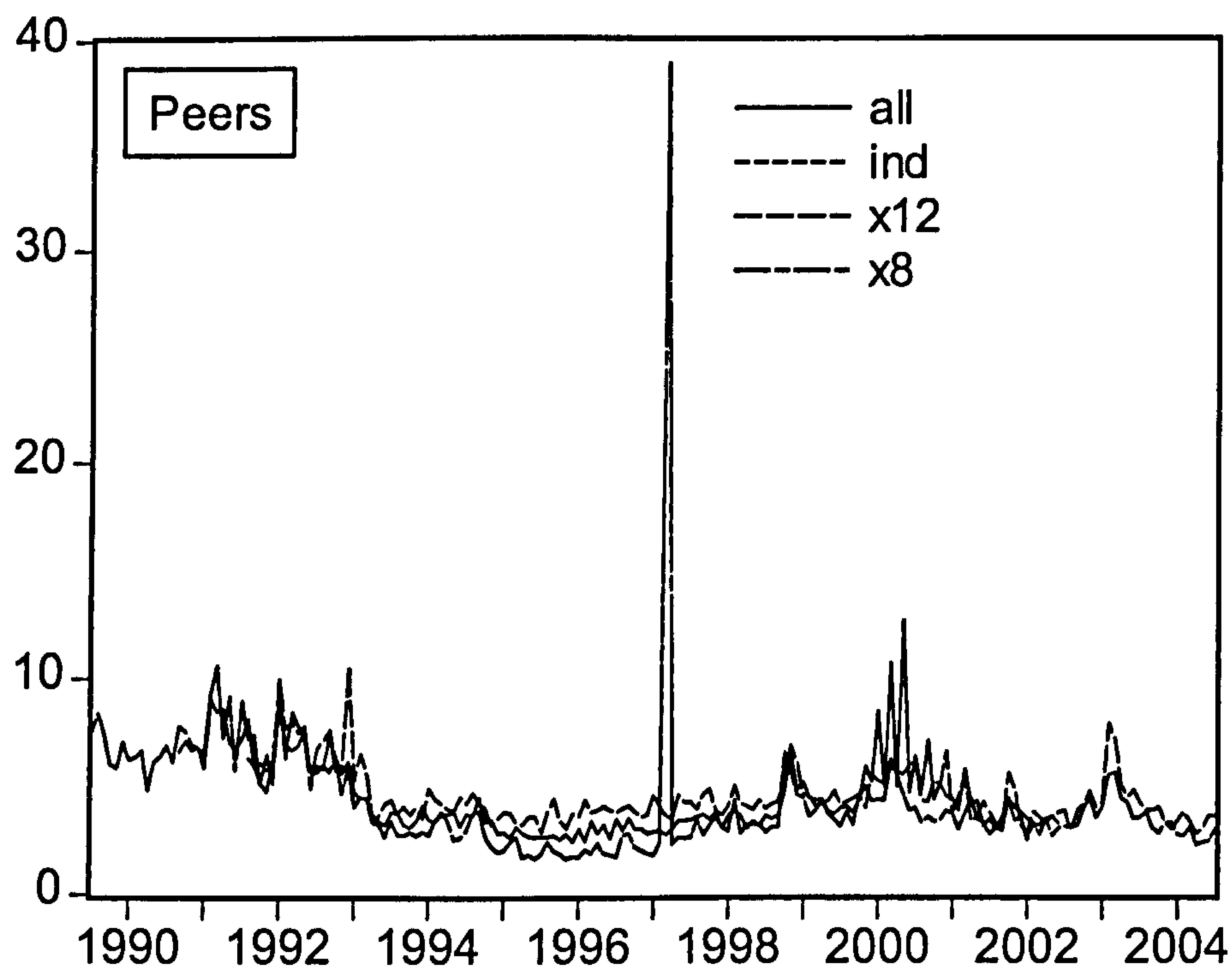


Figure 7-20 SET* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

7.11 IIE* Insight Investment Evergreen Results

7.11.1 IIE* Mean Returns – 'Alpha' α_p

Table 7-19 provides summary information regarding how the mean performance of IIE* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-19 IIE* and Peers: Comparing Alpha

		MARKET				CAPM			
		IIE*	IIE* p	peers	anova p	IIE*	IIE* p	peers	anova p
OWN	all	-0.147	0.439	0.238	0.489	-0.374	0.024	0.226	0.340
	ind	-0.147	0.439	0.170	0.263	-0.374	0.024	0.471	0.476
	x12	-0.142	0.023	0.091	0.169	-0.147	0.121	-0.124	0.982
FTSE	all	-3.917	0.000	-0.259	0.008	-6.118	0.000	-0.319	0.001
	ind	-3.917	0.000	0.050	0.008	-6.118	0.000	0.037	0.003
	x12	-3.936	0.000	-0.047	0.000	-3.751	0.000	-0.113	0.000

Information on IIE* and peers can be found in Table 4-12 on p.49 where it can be seen that IIE* is in the Global Growth investment sector with FTSE World – World benchmark index; at least one of these is also true for each of IIE*'s peers. Therefore comparison with the domestic UK FTSE All Share index is of limited relevance, the lower portion of Table 7-19 being provided mainly for consistency with the reporting of other funds. This is a limitation of the present research that is noted in recommendation 5 of chapter 9 on p.193.

Focussing on the own benchmark – market model results[7] in the top left quadrant of Table 7-19 it is apparent that IIE*'s mean return performance is similar to or, in more recent time sample 'x12', statistically significantly worse than its benchmark index, but indistinguishable from that of its peers. Results under the CAPM do not differ greatly.

7.11.2 IIE* Conditional Variance

Table 7-20 provides summary information regarding the variability of IIE* about the benchmark index and of its peers about the benchmark index, and whether these differ. Interpretation is similar to Table 7-2 on p.112 and is described there.

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[7] See footnote 1 on p.109.

Table 7-20 IIE* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		IIE*	**peers**	**Δ**	**p-value**	**IIE***	**peers**	**Δ**	**p-value**
OWN	**all**	7.394	7.732	0.338	0.705	7.871	7.819	-0.052	0.954
	ind	7.394	3.306	-4.088	0.000	7.871	3.328	-4.543	0.000
	x12	5.709	4.427	-1.282	0.001	5.952	11.497	5.545	0.001
FTSE	**all**	9.758	8.035	-1.722	0.049	9.460	7.799	-1.660	0.061
	ind	9.758	3.665	-6.092	0.000	9.460	3.651	-5.808	0.000
	x12	7.901	4.925	-2.976	0.000	8.199	4.630	-3.568	0.000

Again focussing on the top left quadrant of Table 7-20, IIE* has significantly greater conditional variance than its peers in time samples 'ind' and 'x12', but not in time sample 'all'. Referring to Table 4-15 on p.52 it can be seen that whereas 'ind' contains the 3 closest peers, and 'x12' contains 6, time sample 'all' contains 10 more broadly-defined peers. The results for 'ind' and 'x12' might therefore be a better indication of IIE*'s performance relative to its peers.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-20 are illustrated in Figure 7-21.

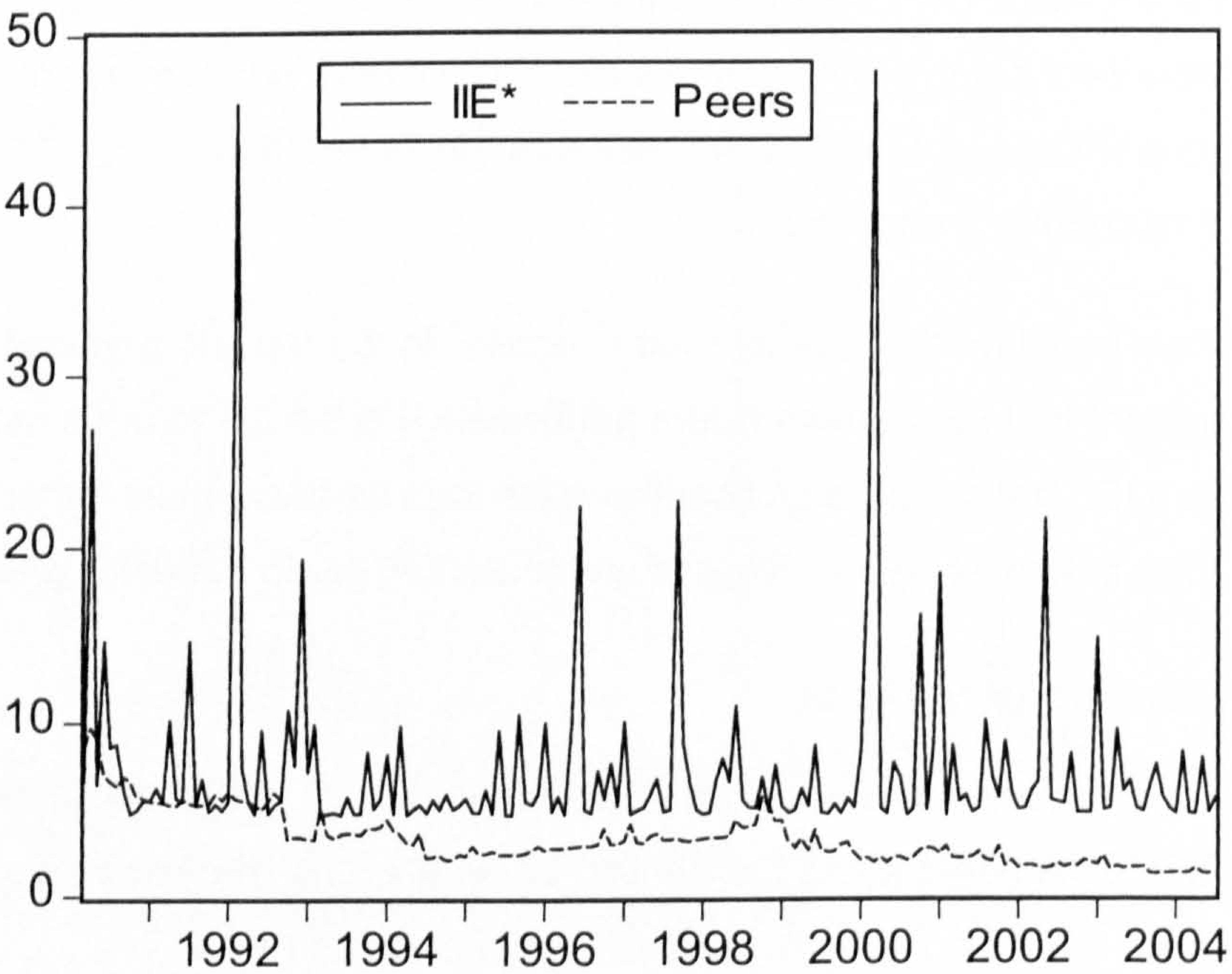


Figure 7-21 IIE* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

In Figure 7-21 the conditional variance of IIE* is not only greater than that of its peers but also more variable, and the difference between the two appears to be increasing over time as the peers' trend is downwards.

7.11.3 IIE* Agreement Between Time Samples

IIE* is effectively estimated over two time samples: 'all'/'ind' and 'x12' with quite different mean conditional variance of 7.394 and 5.709, respectively (shown in Table 7-20 on p.156). Unsurprisingly, the usual anova F-test rejects the null hypothesis of equality of means. The correlation between these two estimated conditional variance series is 0.170.

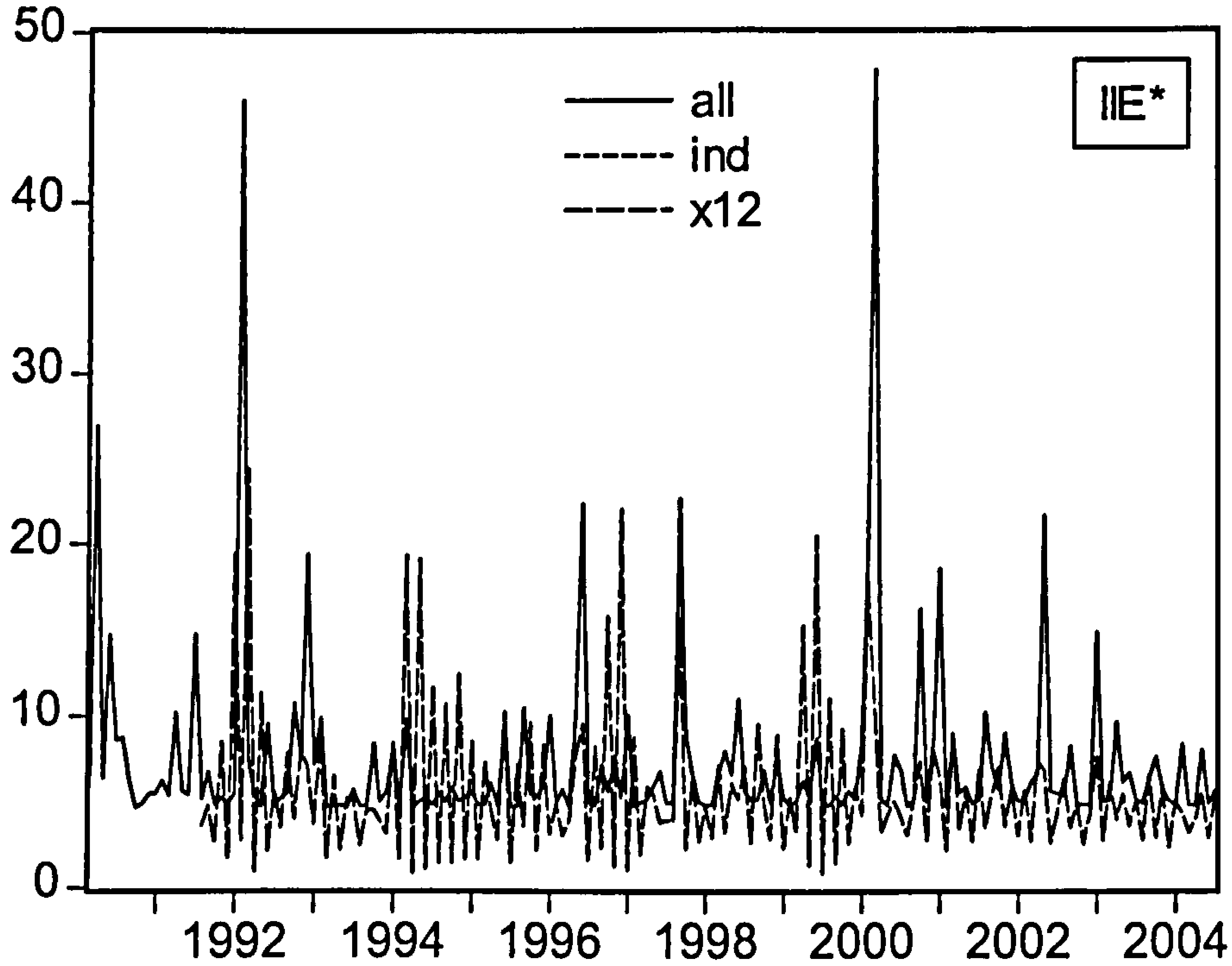
Peer results for the three time samples are distinct, differing as they do not only by time period but also by which candidate peers are included for consideration. Equality of the quite different means is rejected with p = 0.000, and pairwise correlation coefficients vary from 0.339 between 'all' and 'ind' to 0.714 between 'all' and 'x12'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-22.

In the left pane of Figure 7-22 the conditional variance estimates of for IIE* appear perhaps more similar than is suggested by the means and correlation coefficient alone, as much of the difference can be seen to be due to peaks in 'all'/'ind' not shared by 'x12'. All the same, conditional variance estimates for IIE* do appear quite sensitive to the time period analysed.

In the right hand pane of Figure 7-22 the three peer series are quite different reflecting the quite different peer fund membership mentioned in the previous section. It is also notable that 'all' and 'x12' follow each other's movements reasonably closely much of the time, but at different levels.

Despite this variability of conditional variance results from time sample to time sample due changes in time period and in which candidate peers are selected for comparison, an overall conclusion is available: IIE* is more variable than its closer peers.



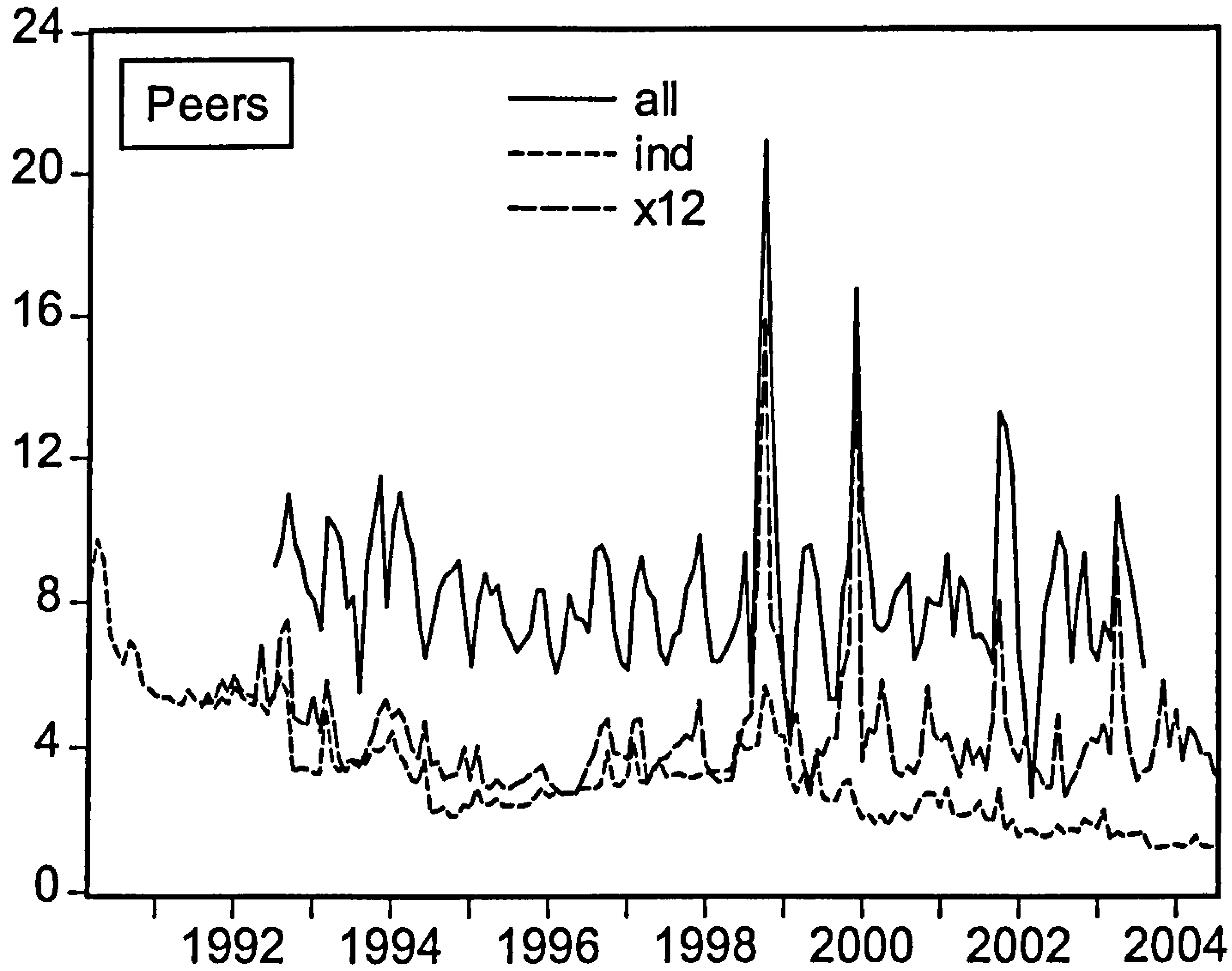


Figure 7-22 IIE* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

7.12 ENV* CIS Environ Results

7.12.1 ENV* Mean Returns – 'Alpha' α_p

Table 7-21 provides summary information regarding how the mean performance of ENV* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-21 ENV* and Peers: Comparing Alpha

		MARKET				CAPM			
		ENV*	**ENV* p**	**peers**	**anova p**	**ENV***	**ENV* p**	**peers**	**anova p**
OWN	**all**	-1.241	0.000	-0.084	0.000	-0.099	0.452	-0.111	0.955
	ind	-1.241	0.000	0.412	0.299	-0.099	0.452	-0.139	0.870
	x12	0.303	0.020	-0.121	0.163	0.068	0.448	-0.159	0.358
FTSE	**all**	-1.241	0.000	0.063	0.019	-0.099	0.452	0.005	0.798
	ind	-1.241	0.000	0.428	0.293	-0.099	0.452	-0.068	0.928
	x12	0.303	0.020	-0.127	0.158	0.068	0.448	-0.169	0.326

Information on ENV* and peers can be found in Table 4-13 on p.50 where it can be seen that although ENV* is in the Global Growth investment sector its benchmark is the domestic UK FTSE All Share index. This accounts for the identical ENV* results in the upper and lower portions of Table 7-21.

In Table 4-15 on p.52 it can be seen that for ENV* time samples 'ind' and 'x12' contain the same peer funds, yet in all four quadrants the mean peer 'alphas' α_p for 'ind' and 'x12' are quite different, due to the time-sample-to-time-sample differences in time period as described in section 4.6 on p.51.

No strong evidence in support of any systematic difference in mean returns between ENV* and the market index or its peers can be found in Table 7-21, as the results vary considerably reflecting sensitivity to choice of time period and/or peers.

7.12.2 ENV* Conditional Variance

Table 7-22 provides summary information regarding how the mean performance of ENV* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-22 ENV* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		ENV*	**peer**	**Δ**	**p-value**	**ENV***	**peer**	**Δ**	**p-value**
OWN	**all**	3.825	2.495	-1.329	0.000	3.141	2.521	-0.620	0.009
	ind	3.825	2.346	-1.479	0.023	3.141	2.480	-0.661	0.345
	x12	2.722	2.088	-0.633	0.001	2.760	2.119	-0.641	0.001
FTSE	**all**	3.825	4.087	0.262	0.467	3.141	4.293	1.152	0.003
	ind	3.825	2.821	-1.003	0.123	3.141	3.052	-0.089	0.901
	x12	2.722	2.586	-0.136	0.546	2.760	2.586	-0.173	0.437

Focussing initially on the results in the top left quadrant of Table 7-22 this provides clear evidence across all three time samples that ENV* is more variable about the FTSE All Share index than are the peers about their own benchmarks.

Examining Table 4-13 on p.50 together with Table 4-15 on p.52 it can be seen that in time samples 'ind' and 'x12' four of the five peers have the FTSE All Share index as 'own' benchmark, while one peer, AXA, has FTSE World – World benchmark. Yet changing the analysis of this one peer, AXA, to use the FTSE All Share index, as in the lower left quadrant of Table 7-22, considerably increases the mean conditional variance across all five peers (e.g. from 2.346 to 2.821 for time sample 'ind'). This effect is sufficient so that the difference between the variability of ENV* and its peers is no longer statistically significantly different from zero. For time sample 'all', where three peers change benchmark, this effect is more pronounced so that the estimated mean peer conditional variance of 4.087 becomes greater than that of ENV* (3.825), although not statistically significantly so.

Unlike some ethical funds previously examined for which comparison with an international benchmark is most appropriate (e.g. JUP*, CFE* and IIE*) the situation regarding ENV* is slightly ambiguous and it is not clear which of the Table 7-22 results are of greatest relevance – those in the top left quadrant or those in the bottom left. Arguably since ENV* "invests mainly in the securities of quoted UK companies and the remainder in quoted overseas securities" it is reasonable to make all comparisons using the FTSE All Share index, in which case the variability of ENV* is not significantly different from that of its peers.

For comparison, mean conditional variance estimates under the CAPM in Table 7-22 follow a similar pattern although the anova tests of equality of mean conditional variance between ENV* and its peers return quite different results.

Following the rationale used for ISG* in section 7.2.2 on p.112, these results from Table 7-20 are illustrated in Figure 7-23.

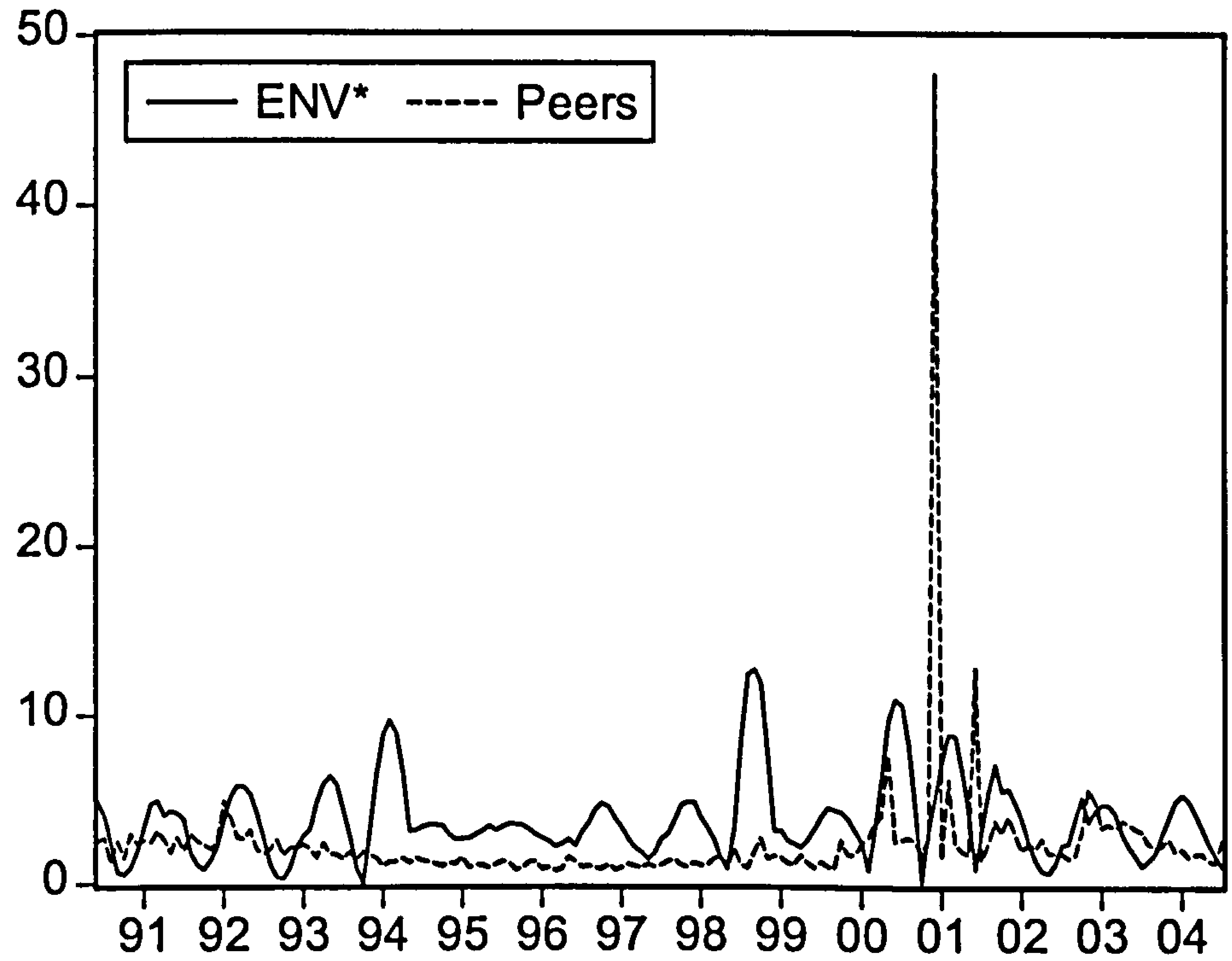


Figure 7-23 ENV* and Peers: Conditional Variance With Own Benchmarks (market model, sample 'ind')

Given the previous comments regarding the use of the FTSE All Share index for comparisons, it is of interest to compare Figure 7-23, in which each fund is assessed against its 'own' benchmark, with a similar graph in which every fund is assessed against the FTSE All Share index, as per Figure 7-24.

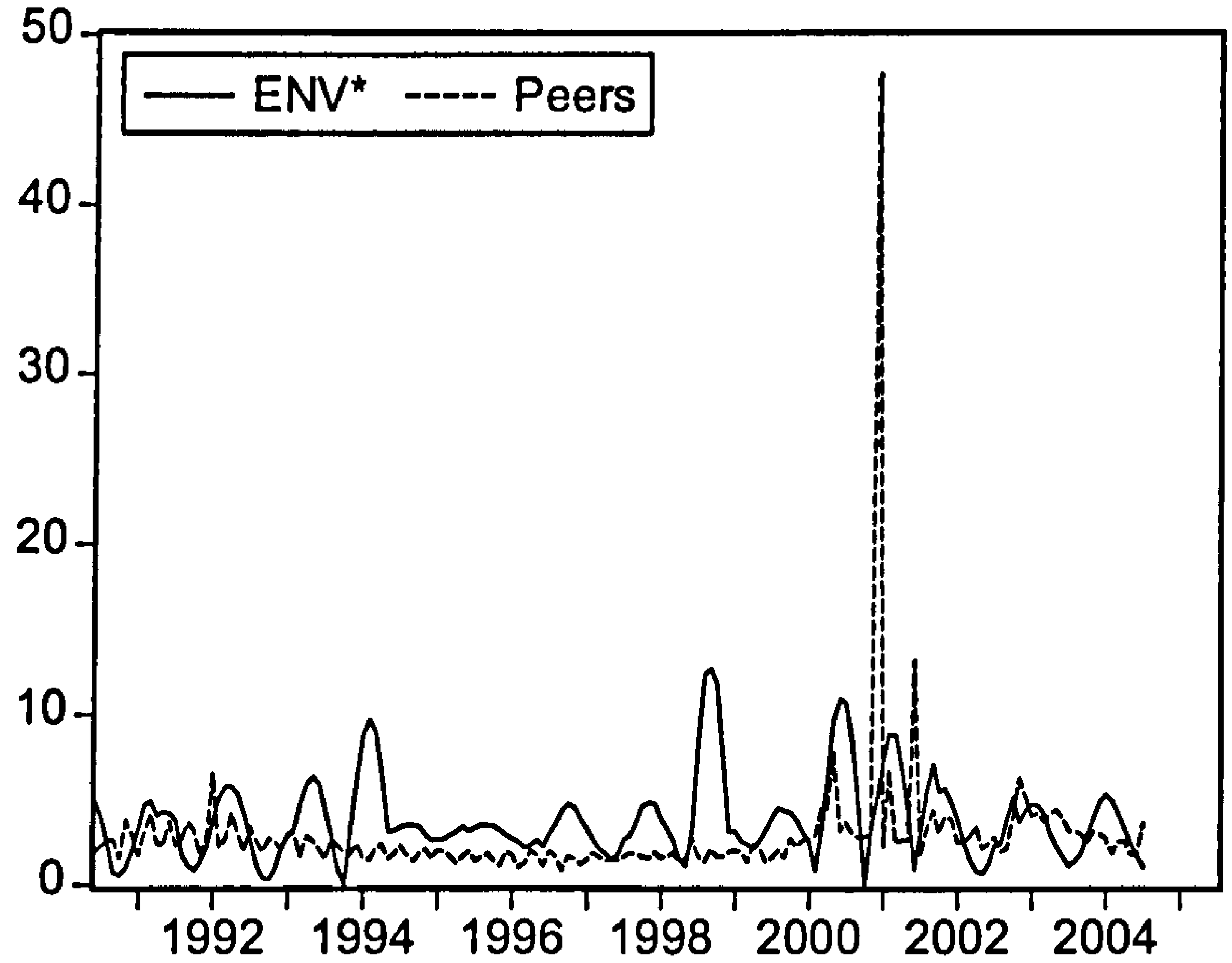


Figure 7-24 As Figure 7-23 But With FTSE All Share Index

Recalling from the discussion above that these two Figures differ only in the results for a single peer fund, AXA, it is perhaps unsurprising to find that they look almost indistinguishable (the ENV* series is identical in both). However, this small change is sufficient to revise the statistically significant difference of -1.479, p = 0.023 in the upper left quadrant of Table 7-22 on p.160 into the statistically insignificant difference of -0.003, p = 0.123 in the lower left quadrant of Table 7-22 on p.160.

7.12.3 ENV* Agreement Between Time Samples

ENV* is effectively estimated over two time samples: 'all'/'ind' and 'x12' with quite different mean conditional variance of 3.825 and 2.722, respectively (shown in Table 7-22 on p.160). Unsurprisingly, the usual anova F-test rejects the null hypothesis of equality of means. The correlation between these two estimated conditional variance series is almost zero: -0.018.

Peer results for the three time samples are distinct although somewhat similar, and the usual anova F-test fails to reject equality of means with p = 0.546. Pairwise correlation coefficients vary from 0.396 between 'all' and 'ind' to 0.779 between 'all' and 'x12'.

The extent of agreement of conditional variance estimates from time sample to time sample is illustrated in Figure 7-25.

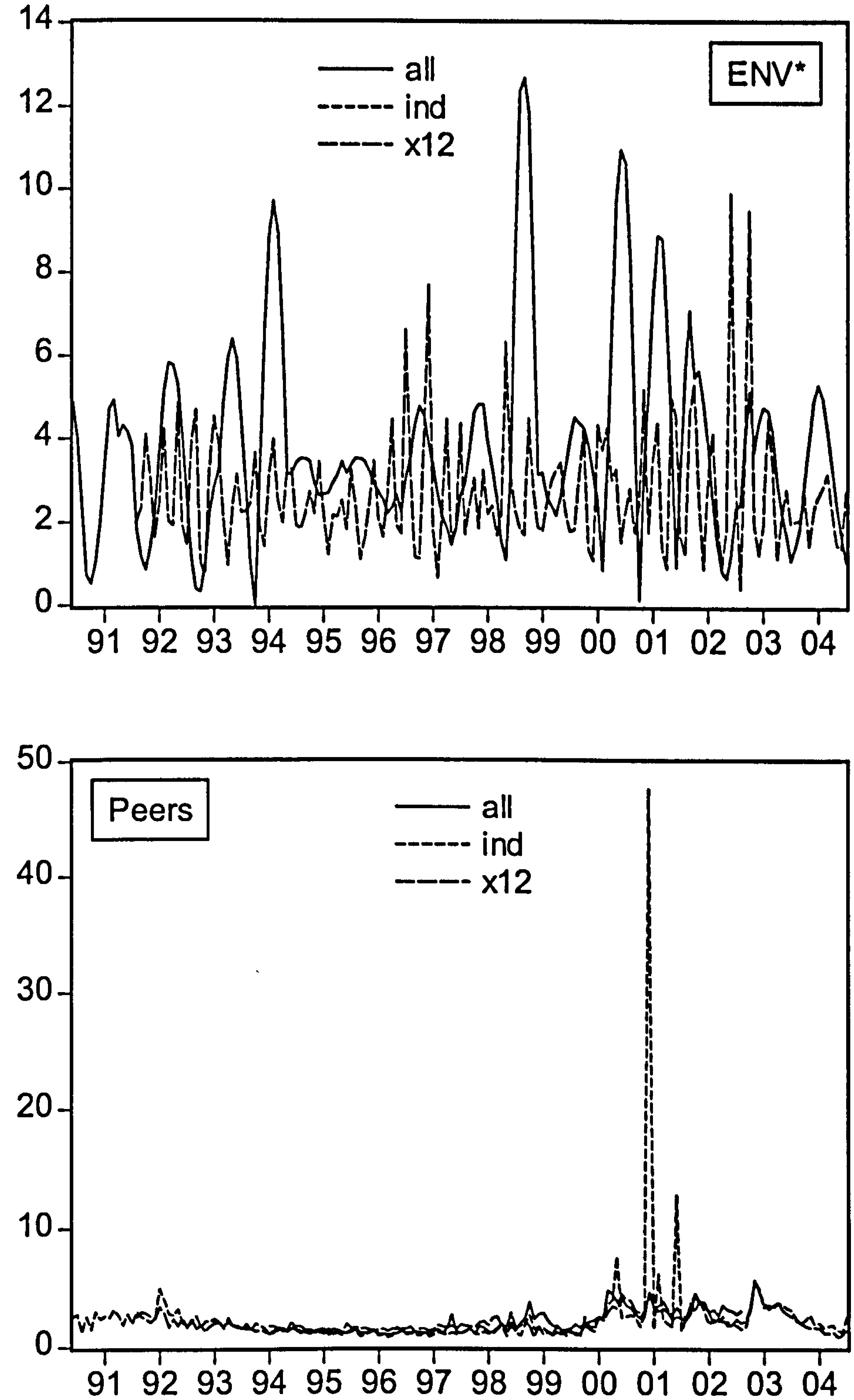


Figure 7-25 ENV* and Peers: Consistency of Conditional Variance Estimates (Own Benchmarks, market model)

In the left hand pane of Figure 7-25 it can be seen that the two ENV* conditional variance estimates 'all'/'ind' and 'x12' actually agree reasonably closely regarding 'quiet' periods and periods of higher volatility, despite the very different means and near-zero correlation of the two series.

In the right hand pane of Figure 7-25 it can be seen that the three series agree reasonably closely except for peaks in 'ind' around 2000. This explains the low correlation coefficient between 'ind' and the other two series.

As explained in section 7.2.3 on p.115 a similar comparison of mean returns (as opposed to conditional variance) using estimated 'alpha' α_p is not possible.

7.13 HGG* Henderson Global Care Growth Results

7.13.1 HGG* Mean Returns – 'Alpha' α_p

Table 7-23 provides summary information regarding how the mean performance of HGG* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-23 HGG* and Peers: Comparing Alpha

		MARKET				CAPM			
		HGG*	**HGG* p**	**peers**	**anova p**	**HGG***	**HGG* p**	**peers**	**anova p**
OWN	**all**	0.190	0.396	0.118	0.766	0.469	0.125	0.049	0.071
	ind	0.190	0.396	0.168	0.930	0.469	0.125	0.080	0.237
	x12	0.190	0.396	0.168	0.930	0.469	0.125	0.080	0.237
FTSE	**all**	0.234	0.222	0.136	0.531	0.192	0.300	0.027	0.512
	ind	0.234	0.222	-0.357	0.540	0.192	0.300	-0.315	0.469
	x12	0.234	0.222	-0.357	0.540	0.192	0.300	-0.315	0.469

For this final ethical fund HGG* the three time samples now converge to the same Aug-91 to Jul-04 time period, and 'ind' and 'x12' include the same three peers while 'all' also includes a fourth, NII (see Table 4-15 on p.52 and Table 4-14 on p.50). Although HGG*'s estimated 'alpha' α_p is positive, it is not statistically significantly different from zero in any instance, nor is it significantly different from that of its peers.

7.13.2 HGG* Conditional Variance

Table 7-24 provides summary information regarding how the mean performance of HGG* compares both to the benchmark index and to its peers. Interpretation is similar to that of Table 7-1 on p.109 and is described there.

Table 7-24 HGG* and Peers: Comparing Mean Conditional Variance

		MARKET				CAPM			
		HGG*	peers	Δ	p-value	HGG*	peers	Δ	p-value
OWN	all	6.858	3.349	-3.509	0.000	7.107	3.570	-3.537	0.000
	ind	6.858	3.952	-2.905	0.000	7.107	4.082	-3.025	0.000
	x12	6.858	3.952	-2.905	0.000	7.107	4.082	-3.025	0.000
FTSE	all	5.285	5.360	0.075	0.873	5.283	5.939	0.656	0.223
	ind	5.285	4.778	-0.507	0.332	5.283	4.725	-0.557	0.272
	x12	5.285	4.778	-0.507	0.332	5.283	4.725	-0.557	0.272

Focussing initially on the top left of Table 7-24 it is clear that under the market model using funds' 'own' benchmarks the variability of HGG* is much higher than that of its peers. Similar results are also obtained under the CAPM in the top right quadrant.

Results in the lower portion of Table 7-24 are more mixed. When assessing all funds relative to the FTSE All Share index, the variability of HGG* falls while that of its peers rises, and the smaller differences are not statistically significantly different from zero.

Which of these results is most relevant is not entirely obvious. In Table 4-14 on p.50 each of HGG* and its peers is either in the Global Growth investment sector or has the FTSE World – World index as benchmark, implying a clear international focus. On the other hand HGG*'s statement of investment objectives is more ambiguous as to the main focus: "investing in a mix of assets including UK and overseas equities" (see section 4.4.12 on p.45).

A cautious approach suggests that while it may indeed be reasonable to compare HGG* with the domestic UK FTSE All Share index, some or all of its peers may have a more unambiguous international focus making comparison with the All Share inappropriate. In the absence of detailed investigation of each fund's investment style, the own benchmark – market model estimates in the top left quadrant of Table 7-24 seem likely to be the more reliable.

HGG*'s conditional variance results can be summarised in a single figure. It is notable in Figure 7-26 that HGG*'s conditional variance exhibits a steady downward trend throughout the period, reaching levels below those of its peers from around 2001 onwards.

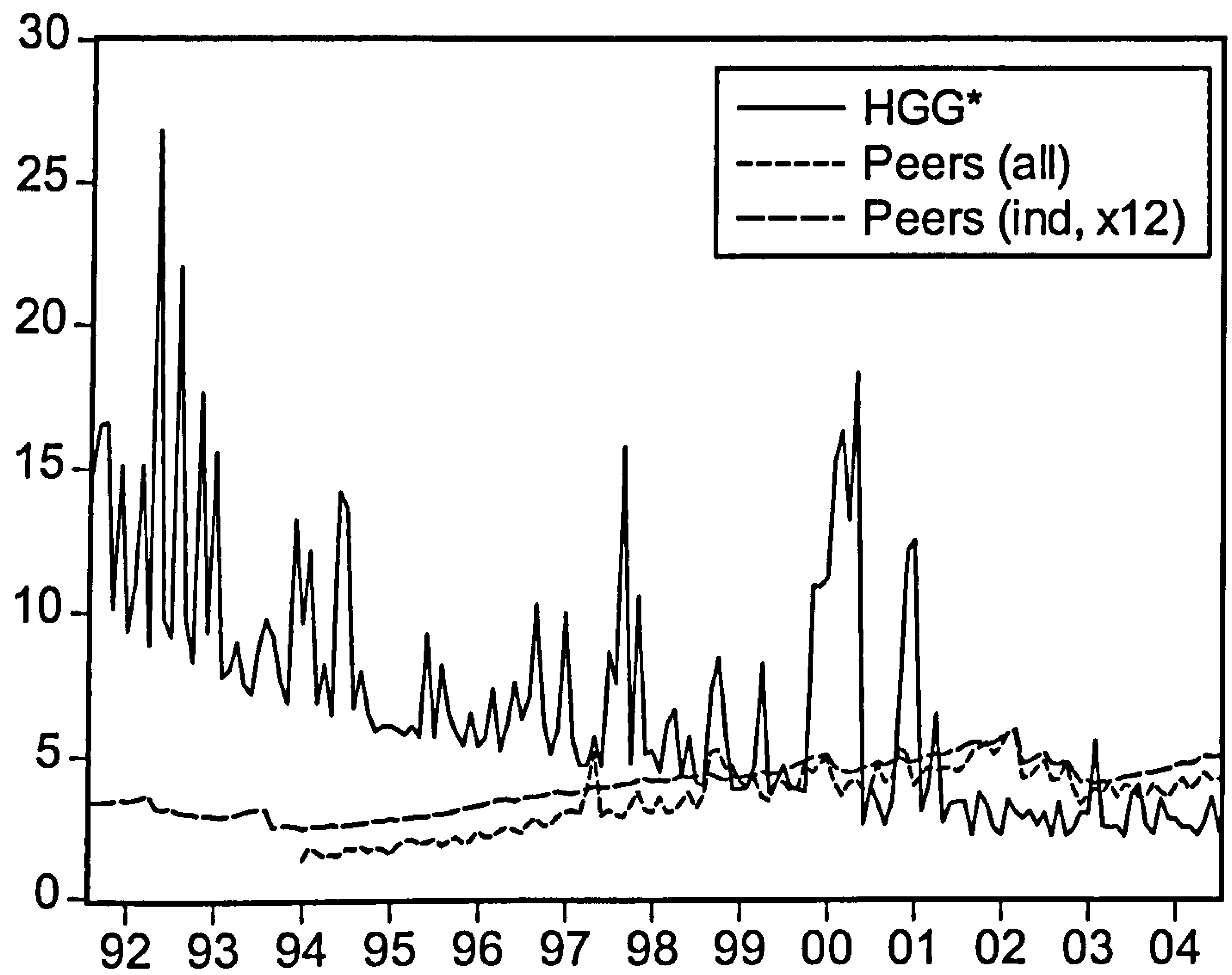


Figure 7-26 HGG* and Peers: Conditional Variance Estimates (Own Benchmarks, market model)

7.13.3 HGG* Agreement Between Time Samples

For this fund there are few estimates to compare. There is a single estimate of HGG* conditional variance common to time samples 'all', 'ind' and 'x12'.

The two mean peer conditional variance estimates for 'all' and 'ind'/'x12' are shown in Figure 7-26 above. The similarity apparent in Figure 7-26 is reflected in a correlation coefficient of 0.934, but the difference between the mean values of 3.503 and 3.952 is highly statistically significantly different from zero with p = 0.000.

7.14 Summary of Individual Ethical Fund Results

The preceding sections 7.2 to 7.13 reporting one-by-one on each of the dozen ethical funds (and their peers) present a diversity of detail that reflects the diversity of investment objectives evident in section 4.4 on p.38 and the diversity of investment sectors and benchmarks evident in section 4.5.2 on p.46. This information does not easily lend itself to a simple answer to the question: do ethical funds perform better or worse than similar conventional funds?

All the same, at the expense of a little oversimplification, a summary is provided in Table 7-25 for market model results and in Table 7-26 for CAPM results. The latter are more in line with previous research. In line with preceding comments regarding the international focus of some funds (for example, JUP*, CFE* and IIE*), attention is also focussed on results using each fund's 'own' benchmark rather than comparing all to a broad UK market index such as the FTSE All Share.

The dozen ethical funds in Table 7-25 are listed in order of launch date, oldest first. The three columns of results in Table 7-25 pertain to the 24 tables in sections 7.2 on p.108 to 7.13 on p.164, focussing only on the market model – own benchmark results in the upper left of these tables. These tables provide information on three different aspects of financial performance, listed in the final three columns of Table 7-25: how the risk-adjusted mean return of an ethical fund compares with its benchmark index ('alpha' α_p), how the risk-adjusted mean return compares with that of its peers (comparing 'alpha' α_p of each fund) and how the variability of an ethical fund about its benchmark index compares with that of its peers (comparing mean conditional variance for each fund).

Table 7-25 Summary of Individual Ethical Fund Results (market model, own benchmarks)

label	fund name	mean return: market	mean return: peers	variability
ISG*	ISIS Stewardship Growth	similar	similar	similar
FRA*	Framlington Health	similar	similar	worse
SWE*	Scottish Widows Ethical	similar	similar	similar
FPS*	Friends Provident Stewardship Income	better	similar	better
AAM*	Allchurches Amity	better	similar	better
JUP*	Jupiter Ecology Fund	better	better	worse
CFE*	City Financial Ethical (Acorn)	similar	similar	similar
AEG*	Aegon Ethical	similar	similar	worse
SET*	Sovereign Ethical	similar	similar	worse
IIE*	Insight Investment Evergreen	worse	similar	worse
ENV*	CIS Environ	similar	similar	worse
HGG*	Henderson Global Care Growth	similar	similar	worse

Table 7-26 Summary of Individual Ethical Fund Results (CAPM, own benchmarks)

label	fund name	mean return: market	mean return: peers	variability
ISG*	ISIS Stewardship Growth	similar	similar	similar
FRA*	Framlington Health	similar	similar	worse
SWE*	Scottish Widows Ethical	similar	similar	similar
FPS*	Friends Provident Stewardship Income	better	similar	similar
AAM*	Allchurches Amity	better	similar	better
JUP*	Jupiter Ecology Fund	better	similar	worse
CFE*	City Financial Ethical (Acorn)	similar	similar	similar
AEG*	Aegon Ethical	similar	similar	worse
SET*	Sovereign Ethical	worse	similar	worse
IIE*	Insight Investment Evergreen	worse	similar	similar
ENV*	CIS Environ	similar	similar	worse
HGG*	Henderson Global Care Growth	similar	similar	worse

Simple rules are applied to the 24 tables of detailed results to allocate one of three descriptors: 'similar', 'worse' or 'better', as follows (but note that this method ignores the magnitude of any effects).

- 'similar': if 'alpha' α_p is not statistically different from zero, or if the difference between the ethical fund and its peers is not statistically different from zero for all time samples analysed, or if there are contradictory statistically significant results from time sample to time sample (some positive, others negative), the ethical fund's performance is described as 'similar'.

- 'better': if 'alpha' α_p is statistically different from zero and positive, or if the difference between the ethical fund and its peers is statistically different from zero and favourable (higher alpha' α_p or lower variance) in half or more of the time samples analysed, the ethical fund's performance is described as 'better'.

- 'worse': if 'alpha' α_p is statistically different from zero and negative, or if the difference between the ethical fund and its peers is statistically different from zero and unfavourable (lower alpha' α_p or higher variance) in half or more of the time samples analysed, the ethical fund's performance is described as 'worse'.

Some patterns are of interest in Table 7-26:

1. Ethical funds tend on the whole to have mean return similar to that of the market index (better in three instances, worse in two instances).

2. An ethical fund has a mean return indistinguishable from that of its peers.

3. The return to an ethical fund is often more variable than its peers (worse in 6 instances, better in one instance)

4. Some, but not all, older ethical funds exhibit performance better than the market and/or better then their peers.

5. More recently launched ethical funds have performance similar to or worse than, but never better than, the market index or their peers.

Of course, these observations refer toTable 7-26, and no evidence regarding wider generalisability is presented here.

7.15 Performance of Ethical Funds as a Group

This section considers whether there are overall tendencies across these dozen ethical funds considered as a (rather diverse) group, firstly, in section 7.15.1, with respect to mean returns as captured by 'alpha' α_p, and then, in section 7.15.2 on p.174, with respect to the variability of returns.

7.15.1 Comparing 'Alpha' α_p of Ethical Funds as a Group

Table 7-27 summarises 'alpha' α_p, results for the market model – own benchmark case[8] from the preceding 12 sections. These results are also illustrated graphically in Figure 7-27 on p.173.

Table 7-27 Comparison of alphas (market model, own benchmark)

		n^E	n^P	mean of α_p			variance of α_p		
				ethical	peer	p-value	ethical	peer	p-value
all	*full*	12	106	-0.027	-0.081	0.886	2.047	1.095	0.025
	significant	4	47	-0.395	-0.191	0.833	3.866	1.638	0.181
ind	*full*	12	57	0.014	0.100	0.832	2.060	1.045	0.018
	significant	6	24	-0.044	0.170	0.812	3.048	1.613	0.161
x4	*full*	4	16	0.728	0.042	0.121	1.026	0.686	0.553
	significant	2	9	1.212	0.027	0.166	1.483	0.930	0.904
x8	*full*	8	45	0.272	-0.136	0.489	1.863	1.464	0.524
	significant	5	20	0.264	-0.135	0.612	2.248	2.212	0.939
x12	*full*	12	77	0.317	-0.024	0.311	0.575	1.135	0.000
	significant	5	43	0.560	-0.101	0.346	0.851	1.516	0.046

In Table 7-27 results are presented for each of the five time samples: 'all', 'ind', etc.

Consider initially time sample 'all'. Results based on 'alpha' α_p estimates for all 12 ethical funds in time sample 'all' are reported in the first row, labelled "full", and this is confirmed in the column headed "n^E" (n being the common symbol for sample size). In time sample 'all' these dozen ethical funds are compared with a total of 106 peer funds, as shown in the next column headed "n^P".

The next three columns in Table 7-27 on p.170 report information on the mean values of the 'alpha' α_p estimates for these two groups of funds (12 ethical, 106 peers).

[8] See footnote 1 on p.109.

Column "ethical" reports the mean value of the dozen estimated ethical fund 'alphas' α_p, -0.027. The next column, "peer" reports the mean value of the corresponding 106 peer 'alpha' α_p estimates: -0.081. The following column, headed "p-value" reports the result of an anova F-test of the null hypothesis of equality of mean across these two groups, and this hypothesis fails to be rejected with p = 0.886. So for time sample 'all', there is no overall mean difference in 'alpha' α_p between the dozen ethical funds and their various peers.

The relevant 'alpha' α_p values for time sample 'all' are summarised graphically in the top left pane of Figure 7-27 on p.173. 'Alpha' α_p is plotted along the horizontal axis and the associated p-value from the regression output of this 'best' GARCH model is plotted on the vertical axis. 'Alphas' α_p of ethical funds are marked with a solid triangle and labelled with the fund name: SET*, etc. 'Alphas' α_p of peer funds are marked with an open circle and are not labelled.

Towards the bottom of the top left pane of Figure 7-27 on p.173 is a shaded region representing p-values less than or equal to 0.05. Conventionally, 'alphas' α_p above this region are judged to be "statistically insignificantly different from zero" – i.e. 'effectively zero', plus or minus a little random error. Markers above this shaded region tend not to be far from the vertical zero axis.

It might be argued that it is not surprising that the previous anova F-test in Table 7-27 on p.170 returned a high p-value of 0.886, since it is seeking to discriminate amongst 'alpha' α_p estimates many of which are 'effectively zero'.

With the preceding point in mind, the anova F-test is repeated considering only those 'alpha' α_p estimates that are statistically significantly different from zero, i.e. with p-values < 0.05. The results are reported in the second row of results for time sample 'all' in Table 7-27 on 170, labelled "significant", for four ethical funds and their 47 peers. It is clear from the top left pane of Figure 7-27 on p.173 that this "significant" sub-sample focuses on the more extreme 'alpha' α_p estimates. However, there is again no significant difference between the ethical funds (with mean value now -0.395) and the peers (-0.191), the anova F-test returning a p-value of 0.833.

Table 7-27 on p.170 reports results obtained from repeating this procedure with the other four time samples 'ind', 'x4', 'x8' and 'x12'. The corresponding 'alpha' α_p estimates are also illustrated graphically in the relevant pane of Figure 7-27 on p.173.

Although a number of 'alpha' α_p estimates for both ethical funds and peers stray considerably from a value of zero (for example, the large negative value of SWE* in time sample 'x8' and the large positive value of AAM* in time sample 'x4') there is never a statistically significant difference between the two groups, as indicated by the absence of shading or borders in the "mean" columns of Table 7-27 on p.170.

The final columns of Table 7-27 on p.170 undertake a similar exercise but testing for any statistically significant difference in the variance of the of 'alpha' α_p estimates of the two groups: ethical funds and peers (again, an F-test is applied). They may both equally be grouped around zero, implying equilibrium mean risk-adjusted returns neither inferior not superior to the market index – but do the 'alpha' α_p estimates of ethical funds vary more (or less) than those of their peers?

In answer to this question Table 7-27 provides contradictory results. In time samples 'all' and 'ind' ethical 'alpha' α_p estimates are significantly more variable than those of their peers, with variance around twice as large. In time sample 'x12' the reverse is the case, with ethical 'alpha' α_p estimates significantly less variable than those of their peers, and in the other two time samples, 'x4' and 'x8' there is no statistically significant difference. These results are illustrated in Figure 7-27 on p.173.

Of the five time samples, 'all' and 'ind' extend the farthest back in time, and 'x12' begins most recently. Thus the results in the final columns of Table 7-27 on p.170 suggest that the 'alpha' α_p estimates of ethical funds have become less variable over time relative to their peers.

The results in this section expand a little on the one-fund-at-a-time summary in Table 7-25 on p.168, where only one ethical fund – JUP* – had superior mean returns compared to its peers. Broadly speaking, it is also the case that taken as a group (with larger sample sizes available for statistical testing), the mean returns of the ethical funds are indistinguishable from those of their peers.

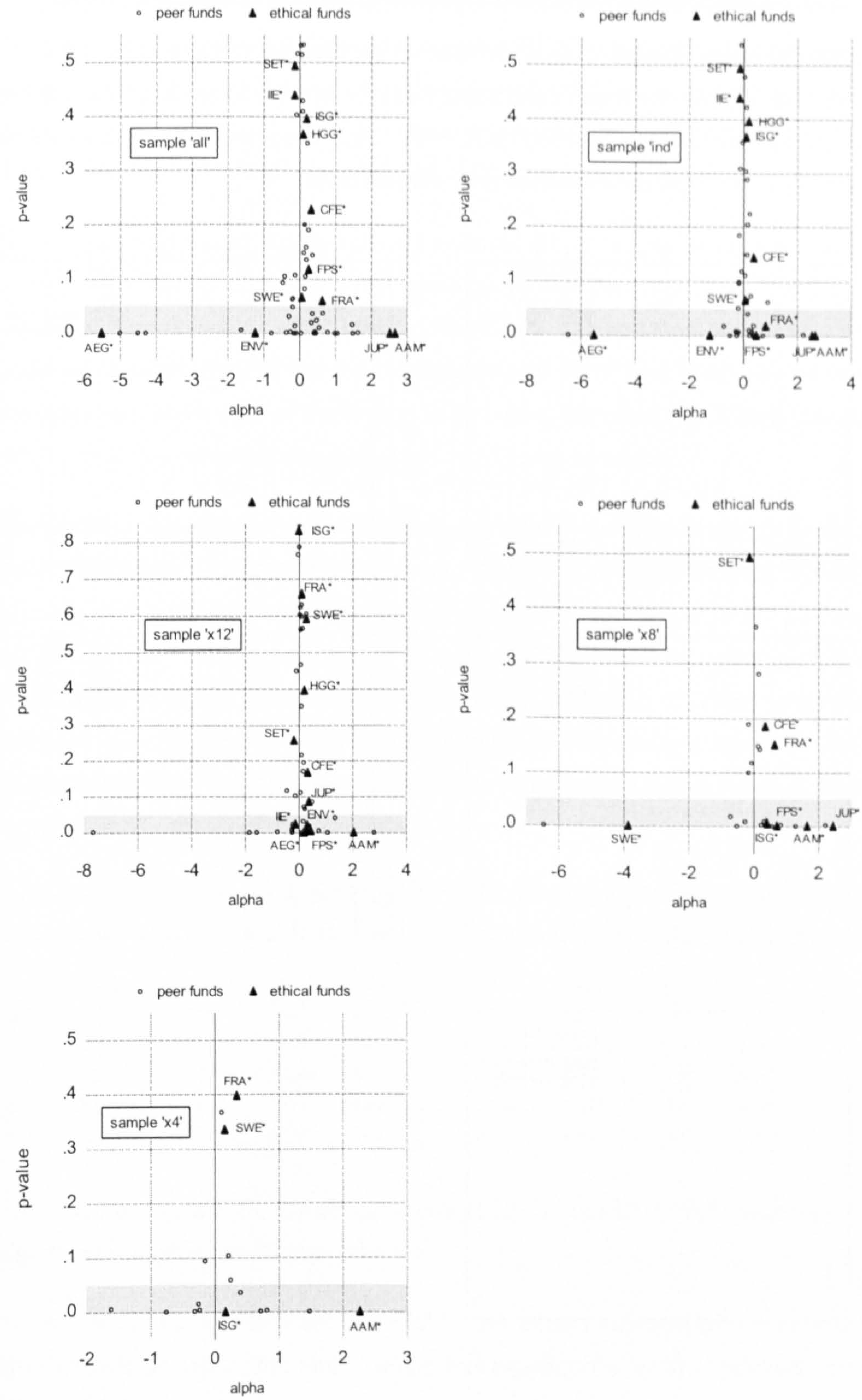


Figure 7-27 'Alpha' α_p: Graphical Summary and Comparison

7.15.2 Comparing Conditional Variance of Ethical Funds as a Group

It is helpful to begin consideration of conditional variance with Figure 7-28. This shows, for each time sample, the mean conditional variance of each fund. Ethical funds have a black vertical bar and are labelled ISG*, FRA*, etc. Their respective peers appear immediately to the right as unlabelled grey vertical bars.

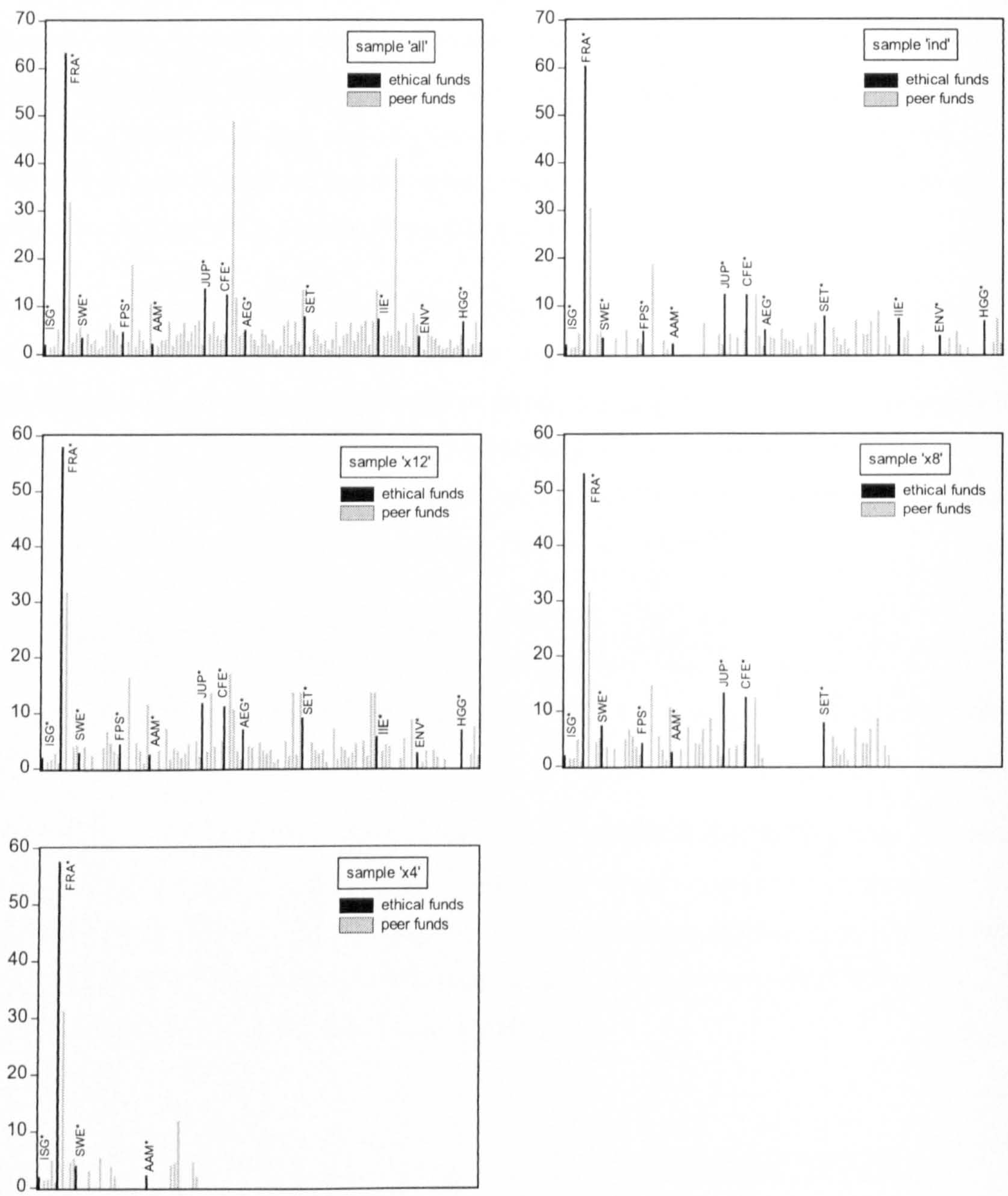


Figure 7-28 Mean Conditional Variance: Graphical Summary and Comparison

The dominant feature in Figure 7-28 is the very high conditional variance of fund FRA*. As explained in section 4.4.2 on p.39, although FRA* is generally listed amongst ethical funds its investment objectives are quite distinct from those of the other eleven ethical funds considered here. It is of interest to have found that its financial performance is also distinctive, in this case variability about the benchmark index.

Some other features of Figure 7-28 are notable. For example, time sample 'all' – the widest interpretation of 'peers' – has some peers with very high mean conditional variance that are lacking in the other more closely matched time samples. Also, the superior (lower) variability ascribed to ethical funds FPS* and AAM* can be seen in that the grey bars to the right of these tend to be higher than their black bars (although FPS* has one peer with particularly high conditional variance).

Table 7-28 provides information on mean conditional variance of ethical funds and peers, taking the ethical funds as a group. Given the above comments regarding the distinctiveness of FRA*, this exercise is also repeated for the group of 11 ethical funds excluding FRA*. In a similar manner to the preceding tables for individual funds, Table 7-28 reports on mean conditional variance across the group of ethical funds ("ethical"), the corresponding figure across the group of peer funds ("peer"), the difference between these two ("Δ") and the outcome ("p-value") of an anova F-test of the null hypothesis of equality of the two means.

Table 7-28 Comparison of Conditional Variance (market model, own benchmark)

	including FRA*				without FRA*			
	ethical	**peer**	**Δ**	**p-value**	**ethical**	**peer**	**Δ**	**p-value**
all	10.178	5.208	-4.970	0.000	6.328	4.959	-1.369	0.000
ind	9.961	4.464	-5.497	0.000	6.293	3.952	-2.341	0.000
x4	15.634	5.536	-10.098	0.000	2.759	3.822	1.063	0.000
x8	12.905	5.197	-7.709	0.000	7.153	4.592	-2.561	0.000
x12	10.356	4.791	-5.565	0.000	6.022	4.459	-1.563	0.000

To the left of Table 7-28, the ethical group of funds, including FRA*, has very significantly higher conditional variance.

To the right of Table 7-28 – without FRA* – this is also the case with the exception of time sample 'x4' where the ethical group has significantly lower conditional variance.

Time sample 'x4' contains the four ethical funds for which the oldest monthly data was available, which, excluding FRA*, are ISG*, SWE* and AAM*. The other four time samples include other more recently launched ethical funds. Therefore Table 7-28 may be indirect evidence that longer-established ethical funds have superior financial performance (lower variability about the market index) to more recently launched ethical funds. This possibility was also raised in Table 7-25 on p.168, and is directly addressed in the next section.

7.16 Cross-Sectional Regression: Age and Size

In this section the relationship, if any, between fund age and/or fund size and financial performance is explored by use of simple cross-sectional regression. This technique has been previously employed by other researchers, notably Gregory et al. (1997) and Kreander et al. (2005) (see section 2.4.1 on p.10).

Firstly, mean returns as measured by 'alpha' α_p are investigated in section 7.16.1. Broadly summarised results presented above in section 7.14 on p.167 were somewhat suggestive of a possible relationship between ethical fund age and mean return although this was not supported by statistical testing in section 7.15.1 on p.170 (as reported in Table 7-27 on p.170).

Secondly, variability of returns is investigated in section 7.16.2 on p.180. Results in both section 7.14 on p. 167 and in section 7.15.2 on p.174 are suggestive of a negative relationship between variability and fund age. Fund age was found to be an important explanatory variable by Gregory et al. (1997) – with longer-established funds performing better – but not by Kreander et al. (2005) whose cross sectional regression had little explanatory power for UK funds. However, both of these authors were examining mean returns are measured by 'alpha' α_p and not variability which the evidence here suggests may be related to fund age.

Fund size has so far been little discussed in the present research, but is positively correlated with fund age and is also a plausible explanatory variable in its own right. Again, this has been used in cross sectional regressions by previous researchers (see section 2.4.1 on p.10).

It was explained in section 2.4.2 on p.16 that the range of explanatory variables used in the present research for cross-sectional regression is a little limited due to constraints of data availability. Other researchers have found additional variables besides the two considered here to be useful, as discussed by Kreander et al. (2005), and this must be acknowledged as a limitation of the present research.

Figure 7-29 shows a scatterplot of fund age and fund size.

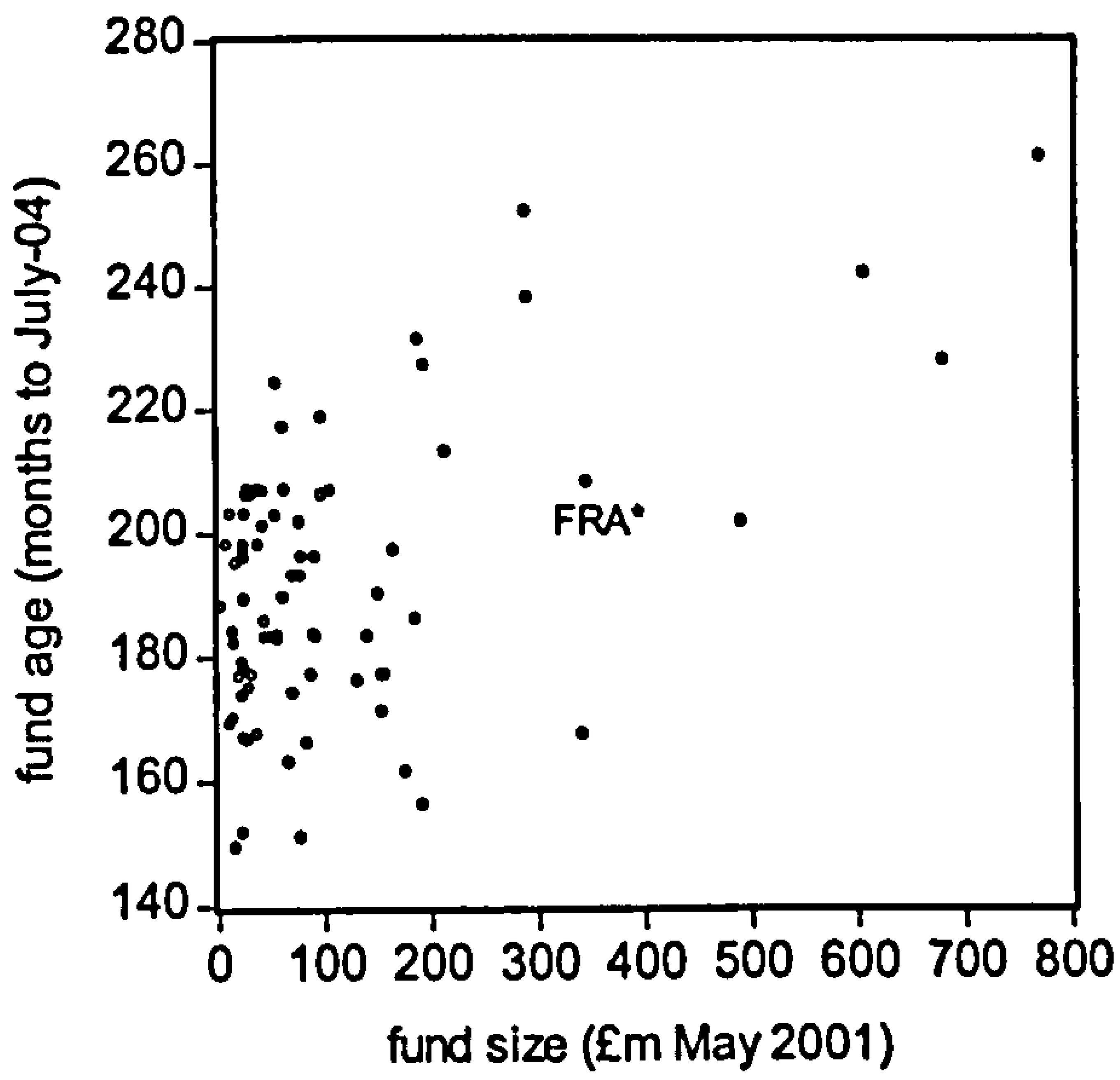


Figure 7-29 Scatterplot of Fund Age and Fund Size

The correlation coefficient across all funds is r = 0.439. However, the correlation between age and size is much stronger for ethical funds: r = 0.638 (peers only: r = 0.412). This reflects the fact that ethical funds tend to be very small and two of the longest-established ethical funds (ISG* and FRA*) are very much larger than the others (see Table 4-2 on p.36).

This high positive correlation between fund age and fund size prompts caution regarding OLS regression models that include both variables. It is well known that such 'collinearity' or 'multicollinearity' leads to inflated standard error estimates as encountered by Luther and Matatko (1994) when seeking to incorporate two market indices into a single model. This is a particular problem with smaller sample sizes as stressed by Gujarati (1995) who goes so far as to say that 'multicollinearity' might also be viewed as a 'micronumerosity' problem (p.326).

With 'multicollinearity' or 'micronumerosity' in mind, the two time samples with the largest available cross-sectional sample size are examined in what follows. Time sample 'all' includes 12 ethical funds matched with 106 conventional funds, giving 118 funds in all – a reasonable sample size. The next largest cross sectional sample is from 'x12' with 89 observations consisting of 12 ethical funds and 77 peers. In section 7.16.2 on p.180 fund FRA* and its peers are excluded (for reasons explained below) giving sample sizes for 'all' and 'x12' of 113 and 84, respectively. Also, caution is exercised in interpreting regression output including both age and size as independent variables.

As has been the case since section 7.14 on p.167, the analysis below is based on market model results using each fund's 'own' benchmark index.

7.16.1 'Alpha' α_p, Size and Age

As a simple starting point, Table 7-29 shows pairwise correlation coefficients between 'alpha' α_p estimated under the market model using funds' own benchmarks and fund age (number of months prior to July 2004 that the fund was launched) and fund size (money under management at the end of May 2001, as used throughout) for time samples 'all' and 'x12'.

Table 7-29 Simple Correlations Between Alpha, Fund Age and Fund Size

	age	size
all	-0.002	0.057
x12	-0.052	-0.042

These correlations are very small and in the case of size have inconsistent sign, suggestive of no (linear) relationship.

A simple cross sectional regression (not shown) of dependent variable 'alpha' α_p with two independent variables fund age and size also finds no relationship. However, this and Table 7-29 do not distinguish between ethical funds and their conventional peers.

It is possible that the 'alpha' α_p of ethical funds is related to fund age and/or size in a way that is different to the relationship (or lack of one) of conventional funds. With this in mind Table 7-30 shows a cross sectional regression including intercept and slope dummy variables to isolate any difference between ethical funds and their peers. (This use of intercept and slope dummy variables in a cross sectional context is very similar to their use with time series data in section 5.2.4 on p.66.)

Table 7-30 'Alpha' α_p Cross Sectional Regression With Fund Age and Size (time sample 'all')

Dependent Variable: 'alpha' α_p
Method: Least Squares
Included observations: 118

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.797626	1.265717	0.630177	0.5299
C(ethical)	-5.852065	4.181665	-1.399458	0.1644
AGE	-0.004897	0.006749	-0.725489	0.4697
AGE(ethical)	0.031815	0.022951	1.386200	0.1684
SIZE	0.000744	0.001125	0.661625	0.5096
SIZE(ethical)	-0.001735	0.002978	-0.582726	0.5612

R-squared	0.021954	Mean dependent var	-0.075309
Adjusted R-squared	-0.021709	S.D. dependent var	1.212712
RSS of regression	1.225805	Akaike info criterion	3.294581
Sum squared resid	168.2908	Schwarz criterion	3.435463
Log likelihood	-188.3803	F-statistic	0.502800
Durbin-Watson stat	2.094867	Prob(F-statistic)	0.773591

Note that in Table 7-30 R^2 is very small and is not statistically significantly different from zero (p = 0.774). Also the p-values from the usual coefficient t-tests (of the null hypothesis of coefficient mean equal to zero) all return values much larger than the conventional 0.05 significance threshold. This is equally true of all ethical dummy variables "AGE(ethical)" etc., and the magnitude of these dummy coefficients is very small.

Table 7-30 shows results for time sample 'all'; those for 'x12' are very similar. Also, bearing in mind the comments above regarding 'multicollinearity', the regression was repeated with age only and with size only, with very similar, insignificant, results.

Recall from section 2.4.1 on p.10 that when performing a similar cross sectional regression, Kreander et al. (2005) note the likelihood of problematic residual serial correlation (which would violate the usual OLS assumption making standard errors and p-values unreliable) and therefore adopt a procedure proposed by Grinblat and Titman (1994) that is robust to this. Here both the Breusch-Godfrey serial correlation LM test (Godfrey 1988) and Ljung-Box Q-statistics (Ljung and Box 1978) from a correlogram of residuals were used to test the null hypothesis of no serial correlation in the model in Table 7-30, and the null hypothesis failed to be rejected by a wide margin. Therefore Table 7-30 reports OLS standard errors and p-values without use of the Grinblat and

Titman (1994) procedure. Similar tests were conducted on all cross sectional regressions reported in this section, with the same outcome.

It seems safe to conclude that the present research finds no relationship between mean returns as measured by 'alpha' α_p and the age or size of a fund. This is equally true of ethical funds and of their non-ethical peers.

7.16.2 Conditional Variance, Size and Age

Table 7-31 shows simple correlation coefficients between mean conditional variance and fund age and size, similarly to Table 7-29 on p.178 for 'alpha' α_p.

Table 7-31 Simple Correlations Between Mean Conditional Variance, Fund Age and Size

	with FRA*		without FRA*	
	age	**size**	**age**	**size**
all	-0.082	-0.051	-0.257	-0.127
x12	0.010	0.136	-0.254	-0.104

Recalling that FRA* is an old, large fund with very high conditional variance untypical of the other ethical funds, correlations are calculated twice: with and without FRA*. (FRA* is the second largest ethical fund - £345m in May-01 - and 5th largest fund including peers, and also the second oldest ethical fund - 208 months before Jul-04 - and 12th oldest fund including peers. This is illustrated in Figure 7-29 on p.177 above.)

To the left of Table 7-31, including FRA*, the correlations are inconsistent between the two time samples, and in three out of four cases are very small. However, the results to the right of Table 7-31, without FRA*, are more interesting. Excluding untypical FRA* there is evidence of a negative association between conditional variance and both age and size, with age having the stronger association.

As in the previous section considering 'alpha' α_p, a cross-sectional regression with ethical dummy variables is informative: see Table 7-32 on p.181.

Comparing Table 7-29 on p.178 ('alpha' α_p) with Table 7-32 on p.181 here, although in the latter R^2 of 0.073 is also small and not statistically significantly different from zero (with p = 0.142) there is a suggestion here of a significant relationship in the statistically significant (p = 0.019) age coefficient of -0.083. In comparison both the size coefficient and the size ethical dummy coefficient have very high p-values (0.772, 0.859).

Table 7-32 Mean Conditional Variance Cross Sectional Regression With Fund Age and Size (time sample 'all', without FRA*)

Dependent Variable: mean conditional variance
Method: Least Squares
Included observations: 113

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.94122	6.515689	3.213969	0.0017
C(ethical)	-8.109627	20.88882	-0.388228	0.6986
AGE	-0.083128	0.034844	-2.385729	0.0188
AGE(ethical)	0.052080	0.114659	0.454218	0.6506
SIZE	-0.001744	0.006013	-0.289968	0.7724
SIZE(ethical)	-0.002761	0.015535	-0.177755	0.8593

R-squared	0.073275	Mean dependent var	5.074501
Adjusted R-squared	0.029970	S.D. dependent var	6.197705
RSS of regression	6.104125	Akaike info criterion	6.507442
Sum squared resid	3986.857	Schwarz criterion	6.652260
Log likelihood	-361.6705	F-statistic	1.692070
Durbin-Watson stat	1.737467	Prob(F-statistic)	0.142714

Bearing in mind the concerns above regarding 'multicollinearity' in the context of the modest sample size here it seems helpful to repeat the regression with only age and dummy variables as independent variables (i.e. removing the size-related variables), as in Table 7-33.

Table 7-33 Mean Conditional Variance Cross Sectional Regression With Fund Age (time sample 'all', without FRA*)

Dependent Variable: mean conditional variance
Method: Least Squares
Included observations: 113

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	21.56872	6.094394	3.539108	0.0006
C(ethical)	-5.305124	17.53224	-0.302592	0.7628
AGE	-0.087103	0.031765	-2.742075	0.0071
AGE(ethical)	0.035036	0.091384	0.383398	0.7022

R-squared	0.071690	Mean dependent var	5.074501
Adjusted R-squared	0.046140	S.D. dependent var	6.197705
RSS of regression	6.053035	Akaike info criterion	6.473753
Sum squared resid	3993.676	Schwarz criterion	6.570298
Log likelihood	-361.7671	F-statistic	2.805889
Durbin-Watson stat	1.710849	Prob(F-statistic)	0.043103

Although the relationship in Table 7-33 is not strong, with $R^2 = 0.072$, it is conventionally statistically significant (p = 0.043), despite the inclusion of two 'redundant' ethical dummy variables (with p-values of 0.763 and 0.702). Estimation without the dummy variables yields a very similar highly significant age coefficient of -0.083, with R^2 highly statistically significantly different from zero with p = 0.006. However, it is useful to see the insignificant dummy variable results in Table 7-33 to illustrate the lack of difference between the ethical funds and their peers.

Table 7-34 repeats Table 7-33 but now for time sample 'x12'.

Table 7-34 Mean Conditional Variance Cross Sectional Regression With Fund Age and Size (time sample 'x12', without FRA*)

Dependent Variable: mean conditional variance
Method: Least Squares
Included observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.10160	4.441932	3.174655	0.0021
C(ethical)	1.432497	10.85746	0.131937	0.8953
AGE	-0.050114	0.022984	-2.180334	0.0320
AGE(ethical)	0.000224	0.056524	0.003969	0.9968

R-squared	0.081498	Mean dependent var	4.654545
Adjusted R-squared	0.048695	S.D. dependent var	3.740189
S.E. of regression	3.647990	Akaike info criterion	5.470619
Sum squared resid	1117.858	Schwarz criterion	5.583225
Log likelihood	-236.7072	F-statistic	2.484425
Durbin-Watson stat	1.829917	Prob(F-statistic)	0.066290

Similarly to Table 7-33 for time sample 'all', Table 7-34 for time sample 'x12' shows a significant negative relationship between mean conditional variance and fund age that is common to both ethical funds and their peers. Although R^2 in Table 7-34 is not statistically significantly different from zero (with p = 0.066), if the equation is re-estimated without the redundant (but illustrative) dummy variables R^2 becomes significant with p = 0.017.

These results are interesting in the light of those of Otten and Bams (2002) who also find a negative relationship between fund age and performance in a sample of 508 European mutual funds. However, Otten and Bams (2002) found this relationship for risk-adjusted mean performance i.e. 'alpha' α_p; here, on the other hand, a similar relationship has been found with variability about the benchmark index, and no relationship with 'alpha' α_p.

7.17 Chapter Conclusions

The financial performance of the dozen ethical funds is not uniform, but varies considerably from fund to fund.

Results have been presented fund-by-fund in detail (sections 7.2 on p. 108 to 7.13 on p.164). Also a simplified overview of the results was derived (section 7.14 on p.167).

Ethical funds FPS* (section 7.5 on p.129) and AAM* (section 7.6 on p.134) stand out as the best performers, with both mean returns consistently above the expected market equilibrium level and also lower variability of returns about the benchmark index than their conventional peers.

JUP* (section 7.7 on p.138) also stands out as a well-performing ethical fund with mean returns superior to the market index. However this appears to be at the expense of greater variability about its benchmark index than its peers. This distinctive financial performance is notable given its distinctive investment objectives (see section 4.4.6 on p.41).

Ethical fund IIE* (section 7.11 on p.155) is notable as a poor performer with mean returns below the expected market equilibrium level and also higher variability of returns around the benchmark index than its non-ethical peers.

Of the remaining eight ethical funds, three: ISG* (section 7.2 on p.108), SWE* (section 7.4 on p.123) and CFE* (section 7.8 on p.143) had financial performance indistinguishable from either the expected market equilibrium level or from their peers. Results for SWE* were sensitive to the choice of 'time sample'.

The remaining five ethical funds: FRA* (section 7.3 on p.118), AEG* (section 7.9 on p.147), SET* (section 7.10 on p.151), ENV* (section 7.12 on p.159) and HGG* (section 7.13 on p.164), had mean returns indistinguishable from either the expected market equilibrium level or from their peers, but variability around the benchmark index was significantly greater than their peers. In the case of fund AEG* estimation of both mean equation parameters and conditional variance were notably sensitive to small changes in the time period analysed.

FRA* deserves special mention as having very much greater variability around its benchmark index than any other fund considered here. Although listed amongst ethical funds it has distinctive financial performance in addition to the distinctive investment objectives previously noted (in section 4.4.2 on p.39). Analysis seeking generalisations regarding the variability of the financial performance of ethical funds should be repeated both with and without FRA*.

Taken together as a group, the mean return to the dozen ethical funds is not different from that of the group of conventional peer funds (section 7.15.1 on p.170). This is consistent with the finding above that only one ethical fund, JUP*, was found to have mean returns significantly different from (better than) its peers.

Taken together as a group (but excluding FRA*), the variability around the benchmark market index of ethical funds tends to be greater than that of the group of conventional peer funds. However, in one sample consisting of longer established ethical funds this variability was found to be less than the corresponding group of peers (section 7.15.2 on p.174, in particular Table 7-28 on p.175).

A small but significant negative relationship was found between fund age and variability of returns around the benchmark index (section 7.16.2 on p.180). This relationship does not differ between ethical and conventional funds i.e. is similar for both groups.

No relationship was found between the mean returns of either ethical funds or conventional funds and fund age or size (section 7.16.1 on p.178).

An attempt at an overall conclusion from the above might be as follows. The evidence suggests that on the whole ethical funds deliver a very similar level of mean financial return to similar conventional funds – occasionally better, rarely worse. A majority of ethical funds examined have greater variability around the benchmark index than similar non-ethical funds, exposing investors to increased risk for a given level of mean return. Since there appears to be a tendency for this variability to be smaller in longer established funds, investing with longer established ethical funds may reduce this risk relative to other ethical funds, but not relative to other similarly long established conventional funds.

8. Conclusions

Recall from section 1.1 on p.1 that the aim of the present research was "to investigate the financial performance of a selection of UK ethical investment funds in comparison to relevant market benchmarks and to similar non-ethical funds".

In pursuit of this general aim four objectives were stated in section 1.2 on p.1, and it is now possible to offer conclusions in relation to each of these. The location within this thesis of the evidence and/or reasoning supporting each conclusion is indicated in parentheses.

8.1 Objective One: Conclusions

- "to review current knowledge and identify research opportunities"

The present research has found that:

Conclusion 1.1 Previous research in this field expresses concern regarding the choice of a common benchmark with which to compare both ethical funds and similar non-ethical funds; a novel approach used here is to compare each fund individually with the index that is listed as most relevant to it (section 2.4.1 on p.10).

Conclusion 1.2 Previous research in this field has examined 'excess returns' using the capital asset pricing model (or variants of this) despite the capital asset pricing model's well-known reliance on assumptions unlikely to fully hold in reality; the market model used here is a less restrictive alternative equilibrium model with some support in the literature (section 2.4.1 on p.10; section 5.2.2 on p.61).[9]

[9] This conclusion requires qualification. The usefulness of the market model as an alternative to the CAPM applies mainly to the variability of returns. When considering mean performance, the CAPM, with its allowance for the availability of risk-free lending and borrowing, is preferable to the market model. In fact, in the present research the main conclusions are not very sensitive to which model is used, as was illustrated in Table 7-25 and Table 7-26 on p.168.

Conclusion 1.3 Most previous research in this field has used a rather restrictive notion of 'similar non-ethical funds' with which to compare ethical funds; a broader approach seems appropriate and is used here (section 2.4.1 on p.10; section 3.3 on p.29; section 4.5 on p.45).

Conclusion 1.4 Recent research in this field has noted the importance of market timing; the search for market timing ability can be broadened by consideration of an additional model not previously used in this field, as done here (section 5.2.2 on p.61).

Conclusion 1.5 Previous research in this field has either ignored the time-varying variance of returns or approached it as a problem requiring 'robust' estimation methods; explicit investigation of the time-varying variance of returns may yield new insights, as here (section 5.3.1 on p.67).

Conclusion 1.6 Previous research in this field has considered funds whose investment objectives remain unchanged; fund Family Charities Ethical presents a rare opportunity to investigate the effect, if any, of adoption of ethical investment principles by a previously 'non-ethical' fund, as is done here (section 3.2 on p.26).

8.2 Objective Two: Conclusions

- "to investigate whether the unusual switch of the Family Charities Ethical fund from conventional to ethical investment objectives affected its financial performance"

The present research has found that:

Conclusion 2.1 Turnover of Family Charities Ethical shareholdings increased around the time of the change in investment objectives, suggesting realignment with the new objectives (Figure 3-1 on p.28).

Conclusion 2.2 The usual measures of fund performance ('alpha' α_p and 'beta' β_p) remained unchanged following Family Charities Ethical's adoption of ethical investment objectives (section 6.5 on p.98).

Conclusion 2.3 The variability of Family Charities Ethical about the benchmark index increased significantly following adoption of ethical investment objectives in March-96 for a period of just over four years (50 months) to May-00 (section 6.5 on p.98).

Conclusion 2.4 An alternative explanation for Family Charities Ethical's temporarily increased variability – that it is due to a change in fund management in Sept-97 – is not well supported by the data (section 6.4 on p.95).

Conclusion 2.5 An alternative explanation that Family Charities Ethical's temporarily increased variability arises due to events or causes external to Family Charities Ethical rather than to the internal change in investment objectives, is also not well supported by the data as no similar change is observed in similar non-ethical funds (section 6.5 on p.98).

Conclusion 2.6 In reaching the previous conclusion, it was helpful to have four similar non-ethical funds with which to compare Family Charities Ethical rather than the single fund used for comparison by previous researchers (section 6.5 on p.98; for previous research see section 2.4 on p.10).

8.3 Objective three: Conclusions

- "to investigate the financial performance of 12 funds that have been ethical since launch"

The present research has found that:

Conclusion 3.1 Although all are 'ethical' the 12 funds do not form a homogeneous group. The Framlington Health fund has investment objectives that conflict directly with those of four other ethical funds and somewhat less so with a further three of the 12 considered here. The Jupiter Ecology fund also has distinct investment objectives, as it is the only one of the 12 that is focussed solely on 'environmental' matters without traditional ethical investment concerns such as avoidance of involvement in the tobacco industry (FRA*, section 4.4.2 on p.39; JUP*, section 4.4.6 on p.41).

Conclusion 3.2 Framlington Health has very much greater variability about its benchmark index than any other ethical fund considered here; this is evidence of a link, as suggested by Cummings (2000), between the financial performance of a fund and the detailed content of its ethical investment objectives (FRA*, section 7.3.2 on p.119).

Conclusion 3.3 Therefore, the inclusion or otherwise of Framlington Health amongst ethical funds being analysed should be carefully considered.

Conclusion 3.4 Jupiter Ecology also has financial performance distinct from the other ethical funds, being the only fund combining mean returns consistently above the expected market equilibrium level with higher variability of returns about the benchmark index than similar non-ethical funds; this is further evidence of a link, as suggested by Cummings (2000), between the financial performance of a fund and the detailed content of its ethical investment objectives. (fund summary Table 7-25 on p.168; detailed JUP* results section 7.7 on p.138).

Conclusion 3.5 The financial performance of the remaining 10 ethical funds varies considerably from fund to fund in ways not obviously related to differences in their (somewhat more homogeneous) investment objectives (chapter 7 on p.108; summary in Table 7-25 on p.168).

Conclusion 3.6 Ethical funds Friends Provident Stewardship Income and Allchurches Amity stand out as the best performers, with both mean returns consistently above the expected market equilibrium level and also variability of returns about the benchmark index either lower than (Allchurches Amity) or similar to (Friends Provident Stewardship) similar non-ethical funds (FPS*, section 7.5 on p.129; AAM*, section 7.6 on p.134).[10]

[10] Based on CAPM results, see summary in Table 7-26 on p.168.

Conclusion 3.7 Ethical funds Insight Investment Evergreen and Sovereign Ethical are notable as poor performers with mean returns below the expected market equilibrium level and variability of returns about the benchmark index either worse than (Sovereign Ethical) or similar to (Insight Investment Evergreen) similar non-ethical funds (IIE*, section 7.11 on p.155; SET*, section 7.10 on p.151).

Conclusion 3.8 Three ethical funds: ISIS Stewardship Growth, Scottish Widows Ethical and City Financial Ethical (Acorn) had financial performance indistinguishable from either the expected market equilibrium level or from similar non-ethical funds (ISG*, section 7.2 on p.108; SWE*, section 7.4 on p.123; CFE*, section 7.8 on p.143).

Conclusion 3.9 Four ethical funds: Framlington Health, Aegon Ethical, Sovereign Ethical, CIS Environ and Henderson Global Care had mean returns indistinguishable from either the expected market equilibrium level or from similar non-ethical funds, but variability about the benchmark index was significantly greater than similar non-ethical funds (FRA*, section 7.3.2 on p.119; AEG*, section 7.9 on p.147; ENV* , section 7.12 on p.159; HGG* , section 7.13 on p.164).

Conclusion 3.10 The best performing ethical funds, Friends Provident Stewardship Income and Allchurches Amity, have consistently low variability about the benchmark index during periods when the variability of similar non-ethical funds increases sharply (Figure 7-9 on p.131; Figure 7-11 on p.135).

Conclusion 3.11 The worst performing ethical funds, Insight Investment Evergreen and Sovereign Ethical, have sharp increases in variability about the benchmark index during periods when the variability of similar non-ethical funds is consistently low or declining (Figure 7-19 on p.152; Figure 7-21 on p.156).

Conclusion 3.12 Taken together as a group, the mean return to the dozen ethical funds is not different from that of a corresponding group of similar non-ethical funds (section 7.15.1 on p.170).

Conclusion 3.13 No relationship was found between the mean returns of either ethical funds or similar non-ethical funds and fund age or fund size (section 7.16.1 on p.178).

Conclusion 3.14 Taken together as a group (both including and excluding Framlington Health) ethical funds have greater variability around the benchmark index than the group of corresponding similar non-ethical funds, with one exception (section 7.15.2 on p.174, in particular Table 7-28 on p.175).

Conclusion 3.15 A group of three longer established ethical funds - ISIS Stewardship Growth, Scottish Widows Ethical and Allchurches Amity had lower variability about the benchmark index than the corresponding group of similar non-ethical funds (section 7.15.2 on p.174, in particular Table 7-28 on p.175).

Conclusion 3.16 A small but significant negative relationship was found between fund age and variability of returns about the benchmark index; this relationship does not differ between ethical funds and similar non-ethical funds (section 7.16.2 on p.180).

Conclusion 3.17 No support is found here for Kreander et al.'s (2005, p.1486) reasonable suggestion that international ethical funds may perform better than those with a domestic focus. Here the better performers are Friends Provident Stewardship Income (UK), Allchurches Amity (UK) and Jupiter Ecology (international), and worst performer is Insight Investment Evergreen (international) (section 7.14 on p.167).

Standing back from the detail, a tentative overall conclusion regarding objective three might be as follows:

Conclusion 3.18 The evidence suggests that on the whole ethical funds deliver a level of mean financial return very similar to non-ethical funds – occasionally better, rarely worse. A majority of ethical funds have variability about the benchmark index greater than that of similar non-ethical funds, exposing investors to increased risk for a given level of mean return. Since there appears to be a tendency for this variability to be smaller in longer established funds, investing with longer established ethical funds may reduce this risk relative to other ethical funds, but not relative to other similarly long established non-ethical funds.

8.4 Objective Four: Conclusions

- "to examine the sensitivity of ethical fund performance measurement to researcher-chosen parameters (choice of equilibrium model, time period analysed, non-ethical funds selected for comparison, how – if at all – variance is modelled)"

The following conclusions are more tentative as this fourth objective was pursued somewhat less thoroughly than the preceding three. Recommendations are also made for further research in chapter 9 on p.193.

Conclusion 4.1 Estimates of mean fund performance ('alpha' α_p) appear to be sensitive to the correct modelling of conditional variance in ways not captured by the use of 'robust' OLS estimation techniques (Table 6-3 on p.94).

Conclusion 4.2 Estimates of mean fund performance ('alpha' α_p) appear to be sensitive to the correct modelling of any temporary changes in conditional variance (Table 6-3 on p.94).

Conclusion 4.3 Often the 'one-size-fits-all' GARCH(1,1) model is sufficient or 'best'; however, estimates of mean fund performance ('alpha' α_p) appear to be sensitive to the correct modelling of conditional variance in ways not always captured by use of a GARCH(1,1) model so that sole use of the GARCH(1,1) model may produce unreliable results (compare AAE* in Table 6-5 on p.99 with AAE* in Table 6-6 on p.104).

Conclusion 4.4 In instances where, as with Allchurches Amity, results remain consistent when analysis is repeated with a different equilibrium return model, over a slightly different time period, or with a broader or narrower set of similar non-ethical funds for comparison; this suggests high confidence in the results (AAM*, section 7.6 on p.134).

Conclusion 4.5 In other instances where, as with Scottish Widows Ethical and Aegon Ethical, results vary and are contradictory when analysis is repeated over a slightly different time period or with a broader or narrower set of non-ethical funds for comparison; this suggests that strong general conclusions are unwarranted (SWE*, section 7.4 on p.123; AEG*, section 7.9 on p.147).

Conclusion 4.6 The preceding points suggest that careful modelling of conditional variance and some form of sensitivity testing with respect to choice of time period and/or choice of similar non-ethical funds may be worthwhile considerations for further research.

9. Recommendations

Recommendations here are of two types.

Firstly come acknowledgements of limitations of the present research: detailed recommendations regarding ways in which the present research might be repeated more in line with other researchers, or repeated with alternative models or additional performance measures, etc.

Secondly come more general recommendations for further research that the conclusions here suggest may prove fruitful.

Detailed Recommendations

Recommendation 1	While the present research does address concerns regarding benchmark choice (by using each fund's individually nominated benchmark – see conclusion 1.1), other methods of doing this are available in the literature and it would be of interest to compare results e.g. using the size-adjusted approach of either Luther and Matatko (1994) or of Gregory et al. (1997).
Recommendation 2	Emphasis is placed in the present research on the use of 'alpha' α_p as a measure of mean risk-adjusted performance; the Sharpe (1966) and Treynor (1965) performance measures might also be calculated for comparison.
Recommendation 3	In the present research market timing is modelled as a means of obtaining reliable 'alpha' α_p estimates but the market timing results themselves are not examined in detail; this may prove worthwhile.
Recommendation 4	Other approaches are available to deal with the problem of standardised residuals that are not normally distributed in addition to the Bollerslev and Wooldridge (1992) 'Heteroscedasticity Consistent Covariance' method used here; it would be of interest to compare results using these other approaches (see section 5.6.2 p.83).

Recommendation 5	The present research analyses each fund both in relation to its own nominated benchmark index and in relation to the broad domestic UK FTSE All Share index; a broad international index may be more appropriate than the FTSE All Share index for some funds with an international focus e.g. Jupiter Ecology.
Recommendation 6	Although the use in the present research of monthly data accords with most previous research in this field, higher frequency data (e.g. the weekly data used by Kreander et al. (2005)) would be advantageous. The resultant larger sample sizes would enable use of post-sample predictive tests for GARCH model selection, as recommended by Alexander (2001, pp.97, 121). Also, ethical funds more recently launched than the 12 considered here would then have sufficient numbers of observations to be included in the analysis.
Recommendation 7	The present research considers data only up to July-04; it would be of interest to update this and also the additional number of observations would enable inclusion of some more recently launched ethical funds.
Recommendation 8	It would be of interest to compare the results of the present research with results obtained using the Carhart (1997) four-factor model employed by Bauer et al (2002, 2003a, 2003b).
Recommendation 9	Apart from conclusions 3.10 and 3.11, most of the results in the present research make use of the mean value of the estimated conditional variance, thus ignoring potentially useful information. There is scope for further analysis. For example, any upward or downward trends or convergence or divergence in the conditional variance of an ethical fund and similar non-ethical funds might be compared.
Recommendation 10	Further cross-sectional explanatory variables (section 7.16 on p.176) should be considered in addition to the rather meagre two - fund age and fund size - used in the present research;

Kreander et al. (2005) provides good discussion of promising explanatory variables.

Recommendation 11 It would be of interest to apply the techniques in the present research to ethical funds in other countries.

General Recommendations

Recommendation 12 The temporary nature of the increase in variability of Family Charities Ethical about the benchmark index (conclusion 2.3) and also the finding that longer established funds have lower variability about the benchmark index (conclusion 3.16) are suggestive of a fund manager 'learning effect' that may merit further investigation as proposed by Bauer et al. (2002, 2003b). In addition to quantitative statistical analysis of the type pursued here, accompanying qualitative research investigating fund managers' experiences, beliefs, attitudes and perceived learning experiences may also prove of interest. This was done in a small way in Mill (2006) (see appendix B on p. 220).

Recommendation 13 Given the non-homogeneity of ethical funds, it would be of interest to investigate further the possibility of differences in investment objectives being associated with differences in financial performance, as found here for the Framlington Health and Jupiter Ecology funds (conclusions 3.2 and 3.4). This would require careful qualitative analysis of investment objectives together with other information such as geographical focus of investment.

Recommendation 14 Conclusion 3.10 above, regarding the consistent and low variability of the best-performing ethical funds, is suggestive and merits further investigation. For example, are the best-performing ethical funds in some way less sensitive to market 'shocks' than are similar non-ethical funds? The present research raises this as a possibility but does not provide good supporting evidence. Were such evidence available it would be of interest to adherents of ethical investment.

Recommendation 15 The cross-sectional (negative) relationship between fund age and variability about the benchmark index (conclusion 3.16) might be further explored by examining the possibility of a time-series relationship between conditional variance and time since fund launch e.g. do longer established funds have lower variability because variability tends to decline over time?

Recommendation 16 Conclusion 4.3 above, regarding possible inaccuracies introduced by use of the 'one-size-fits-all' GARCH(1,1) model in circumstances where a GARCH variant model (e.g. an asymmetric or component model) better describes the data, seems worthy of further systematic investigation.

Recommendation 17 A number of the ethical funds whose performance has been investigated in the present research have also been investigated by previous researchers; a review or meta-analysis of these results may prove illuminating.

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Appendix A: Key To Model Sets

This appendix provides a more detailed key to the model sets described in section 5.5 on p.78 and summarised in Table 5-2 on p.80.

Note that whereas model set M1 lists candidate models for the analysis of the 12 ethical funds and peers considered in chapter 4 on p.34 and chapter 7 on p.108, models sets M2, M3, M4 and M5 are relevant only to the analysis of fund FCE* and its peers as described in chapter 3 on p.26 and chapter 6 on p.89.

Model Set M1

Model set M1 applies to the dozen ethical funds considered in chapter 4 on p.34 and chapter 7 on p.108. 66 varieties of GARCH variance equation are estimated plus an ordinary least squares (OLS) model with no variance equation giving 67 variance equation possibilities. The 66 GARCH variance equations are derived from equations shown in section 5.4 on p.73 by varying the choice of parameters such as lag length and asymmetry order, as described in Table A-1 below.

Each of these 67 variance equations is estimated in combination with each of three mean equation specifications. Firstly, the CAPM of equation (1) on p.62. A second mean equation specification incorporates market timing using the Henriksson and Merton (1981) method of equation (2) on p.63, and a third incorporates market timing using the Treynor and Mazuy (1966) method of equation (3) on p.64.

Three permutations of mean equation paired with 67 permutations of variance equation gives 3 x 67 = 201 different models to estimate. These are listed in Table A-1.

Table A-1: Listing of Model Set M1

	Label	Mean Equation	Variance Equation
1	plain OLS	(1) on p.62	none
2	OLS+tsq	(3) on p.64	none
3	OLS+tdm	(2) on p.63	none
4	ARCH(1)	(1) on p.62	(12) on p.74 with p = 1, q = 0
5	ARCH(1)+tsq	(3) on p.64	(12) on p.74 with p = 1, q = 0
6	ARCH(1)+tdm	(2) on p.63	(12) on p.74 with p = 1, q = 0
7	GARCH(1,1)	(1) on p.62	(12) on p.74 with p = 1, q = 1
8	GARCH(1,1)+tsq	(3) on p.64	(12) on p.74 with p = 1, q = 1

Table A-1: Listing of Model Set M1 (continued)

	Label	Mean Equation	Variance Equation
9	GARCH(1,1)+tdm	(2) on p.63	(12) on p.74 with p = 1, q = 1
10	GARCH(2,1)	(1) on p.62	(12) on p.74 with p = 2, q = 1
11	GARCH(2,1)+tsq	(3) on p.64	(12) on p.74 with p = 2, q = 1
12	GARCH(2,1)+tdm	(2) on p.63	(12) on p.74 with p = 2, q = 1
13	GARCH(1,2)	(1) on p.62	(12) on p.74 with p = 1, q = 2
14	GARCH(1,2)+tsq	(3) on p.64	(12) on p.74 with p = 1, q = 2
15	GARCH(1,2)+tdm	(2) on p.63	(12) on p.74 with p = 1, q = 2
16	GARCH(2,2)	(1) on p.62	(12) on p.74 with p = 2, q = 2
17	GARCH(2,2)+tsq	(3) on p.64	(12) on p.74 with p = 2, q = 2
18	GARCH(2,2)+tdm	(2) on p.63	(12) on p.74 with p = 2, q = 2
19	T1ARCH(1)	(1) on p.62	(14) on p.75 with p = 1, q = 0, r = 1
20	T1ARCH(1)+tsq	(3) on p.64	(14) on p.75 with p = 1, q = 0, r = 1
21	T1ARCH(1)+tdm	(2) on p.63	(14) on p.75 with p = 1, q = 0, r = 1
22	T1ARCH(1,1)	(1) on p.62	(14) on p.75 with p = 1, q = 1, r = 1
23	T1ARCH(1,1)+tsq	(3) on p.64	(14) on p.75 with p = 1, q = 1, r = 1
24	T1ARCH(1,1)+tdm	(2) on p.63	(14) on p.75 with p = 1, q = 1, r = 1
25	T1ARCH(2,1)	(1) on p.62	(14) on p.75 with p = 2, q = 1, r = 1
26	T1ARCH(2,1)+tsq	(3) on p.64	(14) on p.75 with p = 2, q = 1, r = 1
27	T1ARCH(2,1)+tdm	(2) on p.63	(14) on p.75 with p = 2, q = 1, r = 1
28	T1ARCH(1,2)	(1) on p.62	(14) on p.75 with p = 1, q = 2, r = 1
29	T1ARCH(1,2)+tsq	(3) on p.64	(14) on p.75 with p = 1, q = 2, r = 1
30	T1ARCH(1,2)+tdm	(2) on p.63	(14) on p.75 with p = 1, q = 2, r = 1
31	T1ARCH(2,2)	(1) on p.62	(14) on p.75 with p = 2, q = 2, r = 1
32	T1ARCH(2,2)+tsq	(3) on p.64	(14) on p.75 with p = 2, q = 2, r = 1
33	T1ARCH(2,2)+tdm	(2) on p.63	(14) on p.75 with p = 2, q = 2, r = 1
34	T2ARCH(1)	(1) on p.62	(14) on p.75 with p = 1, q = 0, r = 2
35	T2ARCH(1)+tsq	(3) on p.64	(14) on p.75 with p = 1, q = 0, r = 2
36	T2ARCH(1)+tdm	(2) on p.63	(14) on p.75 with p = 1, q = 0, r = 2
37	T2ARCH(1,1)	(1) on p.62	(14) on p.75 with p = 1, q = 1, r = 2
38	T2ARCH(1,1)+tsq	(3) on p.64	(14) on p.75 with p = 1, q = 1, r = 2
39	T2ARCH(1,1)+tdm	(2) on p.63	(14) on p.75 with p = 1, q = 1, r = 2
40	T2ARCH(2,1)	(1) on p.62	(14) on p.75 with p = 2, q = 1, r = 2
41	T2ARCH(2,1)+tsq	(3) on p.64	(14) on p.75 with p = 2, q = 1, r = 2
42	T2ARCH(2,1)+tdm	(2) on p.63	(14) on p.75 with p = 2, q = 1, r = 2
43	T2ARCH(1,2)	(1) on p.62	(14) on p.75 with p = 1, q = 2, r = 2
44	T2ARCH(1,2)+tsq	(3) on p.64	(14) on p.75 with p = 1, q = 2, r = 2
45	T2ARCH(1,2)+tdm	(2) on p.63	(14) on p.75 with p = 1, q = 2, r = 2
46	T2ARCH(2,2)	(1) on p.62	(14) on p.75 with p = 2, q = 2, r = 2
47	T2ARCH(2,2)+tsq	(3) on p.64	(14) on p.75 with p = 2, q = 2, r = 2
48	T2ARCH(2,2)+tdm	(2) on p.63	(14) on p.75 with p = 2, q = 2, r = 2
49	E1GARCH(1)	(1) on p.62	(15) on p.76 with p = 1, q = 0, r = 1
50	E1GARCH(1)+tsq	(3) on p.64	(15) on p.76 with p = 1, q = 0, r = 1
51	E1GARCH(1)+tdm	(2) on p.63	(15) on p.76 with p = 1, q = 0, r = 1
52	E1GARCH(1,1)	(1) on p.62	(15) on p.76 with p = 1, q = 1, r = 1
53	E1GARCH(1,1)+tsq	(3) on p.64	(15) on p.76 with p = 1, q = 1, r = 1
54	E1GARCH(1,1)+tdm	(2) on p.63	(15) on p.76 with p = 1, q = 1, r = 1
55	E1GARCH(2,1)	(1) on p.62	(15) on p.76 with p = 2, q = 1, r = 1
56	E1GARCH(2,1)+tsq	(3) on p.64	(15) on p.76 with p = 2, q = 1, r = 1

Table A-1: Listing of Model Set M1 (continued)

	Label	Mean Equation	Variance Equation
57	E1GARCH(2,1)+tdm	(2) on p.63	(15) on p.76 with p = 2, q = 1, r = 1
58	E1GARCH(1,2)	(1) on p.62	(15) on p.76 with p = 1, q = 2, r = 1
59	E1GARCH(1,2)+tsq	(3) on p.64	(15) on p.76 with p = 1, q = 2, r = 1
60	E1GARCH(1,2)+tdm	(2) on p.63	(15) on p.76 with p = 1, q = 2, r = 1
61	E1GARCH(2,2)	(1) on p.62	(15) on p.76 with p = 2, q = 2, r = 1
62	E1GARCH(2,2)+tsq	(3) on p.64	(15) on p.76 with p = 2, q = 2, r = 1
63	E1GARCH(2,2)+tdm	(2) on p.63	(15) on p.76 with p = 2, q = 2, r = 1
64	E2GARCH(1)	(1) on p.62	(15) on p.76 with p = 1, q = 0, r = 2
65	E2GARCH(1)+tsq	(3) on p.64	(15) on p.76 with p = 1, q = 0, r = 2
66	E2GARCH(1)+tdm	(2) on p.63	(15) on p.76 with p = 1, q = 0, r = 2
67	E2GARCH(1,1)	(1) on p.62	(15) on p.76 with p = 1, q = 1, r = 2
68	E2GARCH(1,1)+tsq	(3) on p.64	(15) on p.76 with p = 1, q = 1, r = 2
69	E2GARCH(1,1)+tdm	(2) on p.63	(15) on p.76 with p = 1, q = 1, r = 2
70	E2GARCH(2,1)	(1) on p.62	(15) on p.76 with p = 2, q = 1, r = 2
71	E2GARCH(2,1)+tsq	(3) on p.64	(15) on p.76 with p = 2, q = 1, r = 2
72	E2GARCH(2,1)+tdm	(2) on p.63	(15) on p.76 with p = 2, q = 1, r = 2
73	E2GARCH(1,2)	(1) on p.62	(15) on p.76 with p = 1, q = 2, r = 2
74	E2GARCH(1,2)+tsq	(3) on p.64	(15) on p.76 with p = 1, q = 2, r = 2
75	E2GARCH(1,2)+tdm	(2) on p.63	(15) on p.76 with p = 1, q = 2, r = 2
76	E2GARCH(2,2)	(1) on p.62	(15) on p.76 with p = 2, q = 2, r = 2
77	E2GARCH(2,2)+tsq	(3) on p.64	(15) on p.76 with p = 2, q = 2, r = 2
78	E2GARCH(2,2)+tdm	(2) on p.63	(15) on p.76 with p = 2, q = 2, r = 2
79	P1ARCH(1)	(1) on p.62	(16) on p.76 with p = 1, q = 0, r = 1
80	P1ARCH(1)+tsq	(3) on p.64	(16) on p.76 with p = 1, q = 0, r = 1
81	P1ARCH(1)+tdm	(2) on p.63	(16) on p.76 with p = 1, q = 0, r = 1
82	P1ARCH(1,1)	(1) on p.62	(16) on p.76 with p = 1, q = 1, r = 1
83	P1ARCH(1,1)+tsq	(3) on p.64	(16) on p.76 with p = 1, q = 1, r = 1
84	P1ARCH(1,1)+tdm	(2) on p.63	(16) on p.76 with p = 1, q = 1, r = 1
85	P1ARCH(2,1)	(1) on p.62	(16) on p.76 with p = 2, q = 1, r = 1
86	P1ARCH(2,1)+tsq	(3) on p.64	(16) on p.76 with p = 2, q = 1, r = 1
87	P1ARCH(2,1)+tdm	(2) on p.63	(16) on p.76 with p = 2, q = 1, r = 1
88	P1ARCH(1,2)	(1) on p.62	(16) on p.76 with p = 1, q = 2, r = 1
89	P1ARCH(1,2)+tsq	(3) on p.64	(16) on p.76 with p = 1, q = 2, r = 1
90	P1ARCH(1,2)+tdm	(2) on p.63	(16) on p.76 with p = 1, q = 2, r = 1
91	P1ARCH(2,2)	(1) on p.62	(16) on p.76 with p = 2, q = 2, r = 1
92	P1ARCH(2,2)+tsq	(3) on p.64	(16) on p.76 with p = 2, q = 2, r = 1
93	P1ARCH(2,2)+tdm	(2) on p.63	(16) on p.76 with p = 2, q = 2, r = 1
94	P2ARCH(1,2)	(1) on p.62	(16) on p.76 with p = 1, q = 2, r = 2
95	P2ARCH(1,2)+tsq	(3) on p.64	(16) on p.76 with p = 1, q = 2, r = 2
96	P2ARCH(1,2)+tdm	(2) on p.63	(16) on p.76 with p = 1, q = 2, r = 2
97	P2ARCH(2,2)	(1) on p.62	(16) on p.76 with p = 2, q = 2, r = 2
98	P2ARCH(2,2)+tsq	(3) on p.64	(16) on p.76 with p = 2, q = 2, r = 2
99	P2ARCH(2,2)+tdm	(2) on p.63	(16) on p.76 with p = 2, q = 2, r = 2
100	ARCH-M(1)	(1) on p.62 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 0
101	ARCH-M(1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 0
102	ARCH-M(1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 0
103	GARCH-M(1,1)	(1) on p.62 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 1

Table A-1: Listing of Model Set M1 (continued)

	Label	Mean Equation	Variance Equation
104	GARCH-M(1,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 1
105	GARCH-M(1,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 1
106	GARCH-M(2,1)	(1) on p.62 plus θ_p from (20) on p.78	(12) on p.74 with p = 2, q = 1
107	GARCH-M(2,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(12) on p.74 with p = 2, q = 1
108	GARCH-M(2,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(12) on p.74 with p = 2, q = 1
109	GARCH-M(1,2)	(1) on p.62 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 2
110	GARCH-M(1,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 2
111	GARCH-M(1,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(12) on p.74 with p = 1, q = 2
112	GARCH-M(2,2)	(1) on p.62 plus θ_p from (20) on p.78	(12) on p.74 with p = 2, q = 2
113	GARCH-M(2,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(12) on p.74 with p = 2, q = 2
114	GARCH-M(2,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(12) on p.74 with p = 2, q = 2
115	T1ARCH-M(1)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 0, r = 1
116	T1ARCH-M(1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 0, r = 1
117	T1ARCH-M(1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 0, r = 1
118	T1ARCH-M(1,1)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 1, r = 1
119	T1ARCH-M(1,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 1, r = 1
120	T1ARCH-M(1,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 1, r = 1
121	T1ARCH-M(2,1)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 1, r = 1
122	T1ARCH-M(2,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 1, r = 1
123	T1ARCH-M(2,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 1, r = 1
124	T1ARCH-M(1,2)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 2, r = 1
125	T1ARCH-M(1,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 2, r = 1
126	T1ARCH-M(1,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 2, r = 1
127	T1ARCH-M(2,2)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 2, r = 1
128	T1ARCH-M(2,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 2, r = 1
129	T1ARCH-M(2,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 2, r = 1
130	T2ARCH-M(1)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 0, r = 2
131	T2ARCH-M(1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 0, r = 2
132	T2ARCH-M(1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 0, r = 2
133	T2ARCH-M(1,1)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 1, r = 2
134	T2ARCH-M(1,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 1, r = 2
135	T2ARCH-M(1,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 1, r = 2
136	T2ARCH-M(2,1)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 1, r = 2
137	T2ARCH-M(2,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 1, r = 2

Table A-1: Listing of Model Set M1 (continued)

	Label	Mean Equation	Variance Equation
138	T2ARCH-M(2,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 1, r = 2
139	T2ARCH-M(1,2)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 2, r = 2
140	T2ARCH-M(1,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 2, r = 2
141	T2ARCH-M(1,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 1, q = 2, r = 2
142	T2ARCH-M(2,2)	(1) on p.62 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 2, r = 2
143	T2ARCH-M(2,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 2, r = 2
144	T2ARCH-M(2,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(14) on p.75 with p = 2, q = 2, r = 2
145	E1GARCH-M(1)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 0, r = 1
146	E1GARCH-M(1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 0, r = 1
147	E1GARCH-M(1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 0, r = 1
148	E1GARCH-M(1,1)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 1, r = 1
149	E1GARCH-M(1,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 1, r = 1
150	E1GARCH-M(1,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 1, r = 1
151	E1GARCH-M(2,1)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 1, r = 1
152	E1GARCH-M(2,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 1, r = 1
153	E1GARCH-M(2,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 1, r = 1
154	E1GARCH-M(1,2)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 2, r = 1
155	E1GARCH-M(1,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 2, r = 1
156	E1GARCH-M(1,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 2, r = 1
157	E1GARCH-M(2,2)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 2, r = 1
158	E1GARCH-M(2,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 2, r = 1
159	E1GARCH-M(2,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 2, r = 1
160	E2GARCH-M(1)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 0, r = 2
161	E2GARCH-M(1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 0, r = 2
162	E2GARCH-M(1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 0, r = 2
163	E2GARCH-M(1,1)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 1, r = 2
164	E2GARCH-M(1,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 1, r = 2
165	E2GARCH-M(1,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 1, r = 2
166	E2GARCH-M(2,1)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 1, r = 2
167	E2GARCH-M(2,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 1, r = 2
168	E2GARCH-M(2,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 1, r = 2
169	E2GARCH-M(1,2)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 2, r = 2
170	E2GARCH-M(1,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 2, r = 2
171	E2GARCH-M(1,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 1, q = 2, r = 2

Table A-1: Listing of Model Set M1 (continued)

	Label	Mean Equation	Variance Equation
172	E2GARCH-M(2,2)	(1) on p.62 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 2, r = 2
173	E2GARCH-M(2,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 2, r = 2
174	E2GARCH-M(2,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(15) on p.76 with p = 2, q = 2, r = 2
175	P1ARCH-M(1)	(1) on p.62 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 0, r = 1
176	P1ARCH-M(1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 0, r = 1
177	P1ARCH-M(1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 0, r = 1
178	P1ARCH-M(1,1)	(1) on p.62 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 1, r = 1
179	P1ARCH-M(1,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 1, r = 1
180	P1ARCH-M(1,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 1, r = 1
181	P1ARCH-M(2,1)	(1) on p.62 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 1, r = 1
182	P1ARCH-M(2,1)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 1, r = 1
183	P1ARCH-M(2,1)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 1, r = 1
184	P1ARCH-M(1,2)	(1) on p.62 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 2, r = 1
185	P1ARCH-M(1,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 2, r = 1
186	P1ARCH-M(1,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 2, r = 1
187	P1ARCH-M(2,2)	(1) on p.62 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 2, r = 1
188	P1ARCH-M(2,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 2, r = 1
189	P1ARCH-M(2,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 2, r = 1
190	P2ARCH-M(1,2)	(1) on p.62 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 2, r = 2
191	P2ARCH-M(1,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 2, r = 2
192	P2ARCH-M(1,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(16) on p.76 with p = 1, q = 2, r = 2
193	P2ARCH-M(2,2)	(1) on p.62 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 2, r = 2
194	P2ARCH-M(2,2)+tsq	(3) on p.64 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 2, r = 2
195	P2ARCH-M(2,2)+tdm	(2) on p.63 plus θ_p from (20) on p.78	(16) on p.76 with p = 2, q = 2, r = 2
196	COMP	(1) on p.62	(18) and (19) on p.77 and p.78
197	COMP+tsq	(3) on p.64	(18) and (19) on p.77 and p.78
198	COMP+tdm	(2) on p.63	(18) and (19) on p.77 and p.78
199	ASCO	(1) on p.62	(18) and (19) on p.77 and p.78 plus η_k with r = 1 from (14) on p.75
200	ASCO+tsq	(3) on p.64	(18) and (19) on p.77 and p.78 plus η_k with r = 1 from (14) on p.75
201	ASCO+tdm	(2) on p.63	(18) and (19) on p.77 and p.78 plus η_k with r = 1 from (14) on p.75

Model Set M2

Model set M2 applies to FCE* and peers only. It takes the 201 models in model set M1 above, and estimates amended versions of these 201 models 15 times, each pass through the 201 models with a different permutation of event dummy variables involving the addition of one, two, three or no dummy variable terms.

Completeness requires 15 passes through (amended versions of) the 201 models in model set M1 as follows.

Event dummy variable possibilities are: mean equation intercept dummy a_1^E (equation (5) on p.62), variance equation slope dummy b_1^E (equation (5) on p.62) and variance equation intercept dummy γ_E (equation (13) on p.71). These can be combined in seven different ways (three single variables, three pairs, plus all three).

Here "E" denotes 'ethical dummy variable coefficient' in combination with a dummy variable starting from Mar-96 when the change in investment objectives occurred. Also of interest is the change of fund management in Sept-97. Using a dummy variable starting from Sept-97 in an entirely similar way there are a further six permutations of models including management dummy variable coefficients a_1^M, b_1^M and γ_M where now "M" denotes 'management dummy variable coefficient'.

The two sets of seven permutations of event dummy variables plus a pass through the 201 models in model set M1 with no event dummy variables gives 15 passes through the 201 models in model set M1. Thus model set M2 contains 15 x 201 = 3015 models.

The makeup of model set M3 is illustrated in Table A-2 below.

Table A-2: Key to Model Set M2 (15 Passes Through Model Set M1)

Pass	Mean Equation	Variance Equation	Number Of Models	Notes
		No Event Dummies		
1	as M1; no event dummies	as M1; no event dummies	201	all of M1
		Ethical Event Dummies		
2	as M1 plus a_1^E from (5) on p.66	as M1; no event dummies	201	all of M1
3	as M1 plus b_1^E from (5) on p.66	as M1; no event dummies	201	all of M1
4	as M1; no event dummies	as M1 plus γ_E from (13) on p.75	201	all of M1
5	as M1 plus a_1^E and b_1^E from (5) on p.66	as M1; no event dummies	201	all of M1
6	as M1 plus a_1^E from (5) on p.66	as M1 plus γ_E from (13) on p.75	201	all of M1
7	as M1 plus b_1^E from (5) on p.66	as M1 plus γ_E from (13) on p.75	201	all of M1
8	as M1 plus a_1^E and b_1^E from (5) on p.66	as M1 plus γ_E from (13) on p.75	201	all of M1
		Management Event Dummies		
9	as M1 plus a_1^M from (5) on p.66	as M1; no event dummies	201	all of M1
10	as M1 plus b_1^M from (5) on p.66	as M1; no event dummies	201	all of M1
11	as M1; no event dummies	as M1 plus γ_M from (13) on p.75	201	all of M1
12	as M1 plus a_1^M and b_1^M from (5) on p.66	as M1; no event dummies	201	all of M1
13	as M1 plus a_1^M from (5) on p.66	as M1 plus γ_M from (13) on p.75	201	all of M1
14	as M1 plus b_1^M from (5) on p.66	as M1 plus γ_M from (13) on p.75	201	all of M1
15	as M1 plus a_1^M and b_1^M from (5) on p.66	as M1 plus γ_M from (13) on p.75	201	all of M1

Total number of models in set M2 = 15 x 201 = 3015

Model Set M3

Model set M3 applies to FCE* and peers only. As described towards the end of section 5.5 on p.78, problems were initially encountered in estimating all 3015 models in model set M2.

Recall that this figure of 3015 for model set M3 arises as a consequence of taking the 201 models in set M1 and repeating these with inclusion of all 15 permutations of the event dummy variables. Therefore the logical way to reduce the number of candidate models down from 3015 is to select a subset of the 201 in model set M1 to be combined with the 15 event dummy variable permutations. In fact a subset of only three models is appropriate – those models with a GARCH(1,1) variance equation either without a timing coefficient in the mean equation, or with one of the two timing coefficients (Henriksson and Merton (1981) as per equation (2) on p.63, Treynor and Mazuy (1966) as per equation (3) on p.64) in the mean equation. These three models are listed as model numbers 7, 8 and 9 in Table A-1 above.

The situation regarding model set M3 is therefore similar to that for M2 described above in Table A-2. This can be seen in Table A-3.

Table A-3: Key to Model Set M3 (15 Passes Through Three Models From Set M1)

Pass	Mean Equation	Variance Equation	Number Of Models	Notes
	No Event Dummies			
1	as M1; no event dummies	as M1; no event dummies	3	7, 8 and 9 from M1
	Ethical Event Dummies			
2	as M1 plus a_1^E from (5) on p.66	as M1; no event dummies	3	7, 8 and 9 from M1
3	as M1 plus b_1^E from (5) on p.66	as M1; no event dummies	3	7, 8 and 9 from M1
4	as M1; no event dummies	as M1 plus γ_E from (13) on p.75	3	7, 8 and 9 from M1
5	as M1 plus a_1^E and b_1^E from (5) on p.66	as M1; no event dummies	3	7, 8 and 9 from M1
6	as M1 plus a_1^E from (5) on p.66	as M1 plus γ_E from (13) on p.75	3	7, 8 and 9 from M1
7	as M1 plus b_1^E from (5) on p.66	as M1 plus γ_E from (13) on p.75	3	7, 8 and 9 from M1
8	as M1 plus a_1^E and b_1^E from (5) on p.66	as M1 plus γ_E from (13) on p.75	3	7, 8 and 9 from M1
	Management Event Dummies			
9	as M1 plus a_1^M from (5) on p.66	as M1; no event dummies	3	7, 8 and 9 from M1
10	as M1 plus b_1^M from (5) on p.66	as M1; no event dummies	3	7, 8 and 9 from M1
11	as M1; no event dummies	as M1 plus γ_M from (13) on p.75	3	7, 8 and 9 from M1
12	as M1 plus a_1^M and b_1^M from (5) on p.66	as M1; no event dummies	3	7, 8 and 9 from M1
13	as M1 plus a_1^M from (5) on p.66	as M1 plus γ_M from (13) on p.75	3	7, 8 and 9 from M1
14	as M1 plus b_1^M from (5) on p.66	as M1 plus γ_M from (13) on p.75	3	7, 8 and 9 from M1
15	as M1 plus a_1^M and b_1^M from (5) on p.66	as M1 plus γ_M from (13) on p.75	3	7, 8 and 9 from M1

Total number of models in set M3 = 15 x 3 = 45

Model Sets M4 and M5

Model sets M4 and M5 apply to FCE* and peers only. These are subsets of model set M3.

In section 6.3 on p.91 the analysis is concerned only with ethical event dummy variables, and not with management event dummy variables. Therefore 'passes' 9 to 15 in the lower portion of Table A-3 above, featuring management event dummy variables, are not relevant. This leaves 'passes' 1 to 8 (with permutations of the ethical dummy variables) giving a total of 8 x 3 = 24 candidate models.

Similarly in section 6.4 on p.95 the analysis is concerned only with management dummy variables so that 'passes' 2 to 8 in Table A-3 above are not relevant, again giving 8 x 3 = 24 candidate models.

Appendix B: Model Selection Results

To illustrate the model estimation and selection process, this appendix provides Eviews output showing the 201 candidate models from which the 'best' is selected according to the criteria described in section 5.6 on p.82. Results in this appendix are from time sample 'ind' only, using the CAPM mean equation with each fund's 'own' benchmark.

There follows two sizeable tables providing two examples of model selection.

The first, Table B-1 for fund ISG*, lists output from the 201 candidate models from which a 'best' GARCH(1,1) model was selected.

The second, Table B-2 for fund SWE*, again lists the 201 candidate models but now an EGARCH(2,2) with asymmetry of order 2 and with a significant Henriksson and Merton (1981) timing term in the mean equation as per equation (2) on p.63 is 'best'.

Note that output below uses the standard notation provided by Eviews and variable names as used in the batch programs. This differs a little from the symbols used in the main text of the thesis, but corresponds in simple ways e.g. RESID(-1)^2 refers to an ARCH term i.e. the first lag of a squared mean-equation residual.

Models in this appendix are listed in the same order as in Table A-1 in Appendix A above, where more information on the specification of each model can be found.

Full estimation output is available from Greig Mill on request as gmill@dmu.ac.uk.

ISG* ISIS Stewardship Growth Model Output

The model selected as 'best' was GARCH(1,1). Table B-1 below provides summary output for all 201 candidate models in model set M1 described in Appendix A: Key To Model Sets on p.210, including the 'best' which is highlighted by shading (listed seventh in Table B-1).

Note that some models fail to converge or otherwise generate errors during estimation and are thus excluded from consideration as a candidate 'best' model.

In Table B-1 "ZHG" refers to the Hoare Govett smallet companies index, the benchmark for ISG*, so that this coefficient is the estimated 'beta'.

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted

Fund: ISG*	plain OLS	sample ind					
: Z1	M1	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0377	0.7372	0.7122	0.026	0.027
s.e.	1.6244	ZHG	0.7854	0.0000	0.0000	0.062	0.080
AIC	3.8176					0.123	0.132
SBC	3.8495					0.215	0.274
J-Bera	0.0000					0.232	0.324
						0.252	0.405
						0.348	0.517
						0.449	0.618

Fund: ISG*	OLS+tsq	sample ind					
: Z1	M2	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8780	C	0.1468	0.2444	0.2748	0.003	0.003
s.e.	1.5932	ZHG	0.7628	0.0000	0.0000	0.010	0.013
AIC	3.7836	ZHG^2	-0.0061	0.0027	0.0630	0.012	0.012
SBC	3.8314					0.025	0.051
J-Bera	0.4284					0.015	0.042
						0.012	0.061
						0.022	0.103
						0.024	0.084

Fund: ISG*	OLS+tdm	sample ind					
: Z1	M3	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	C	0.2474	0.1396	0.1715	0.001	0.002
s.e.	1.6080	ZHG	0.8473	0.0000	0.0000	0.004	0.007
AIC	3.8021	ZHG*ZHG_TM	-0.1422	0.0230	0.0987	0.007	0.008
SBC	3.8499					0.016	0.027
J-Bera	0.0402					0.012	0.034
						0.010	0.050
						0.018	0.083
						0.028	0.108

ARCH(1)
M4
Errors generated – model rejected

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

ARCH(1)+tsq
M5

Errors generated – model rejected

ARCH(1)+tdm
M6

Errors generated – model rejected

Fund: ISG*	GARCH(1,1)	sample ind					
: Z1	M7	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8717	C	-0.0465	0.6604	0.6035	0.168	0.172
s.e.	1.6419	ZHG	0.7605	0.0000	0.0000	0.344	0.377
AIC	3.7320	C	0.0597	0.0244	0.2168	0.300	0.296
SBC	3.8117	RESID(-1)^2	-0.0469	0.0032	0.0358	0.389	0.427
J-Bera	0.6185	GARCH(-1)	1.0206	0.0000	0.0000	0.354	0.352
						0.477	0.463
						0.491	0.454
						0.531	0.422

GARCH(1,1)+tsq
M8

Errors generated – model rejected

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	GARCH(1,1)+tdm	sample ind					
: Z1	M9	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8754	C	0.2041	0.2724	0.1851	0.199	0.203
s.e.	1.6216	ZHG	0.8336	0.0000	0.0000	0.393	0.424
AIC	3.7386	ZHG*ZHG_TM	-0.1378	0.0077	0.0703	0.216	0.209
SBC	3.8342	C	0.0547	0.0482	0.0028	0.306	0.339
J-Bera	0.7917	RESID(-1)^2	-0.0411	0.0000	0.0191	0.300	0.312
		GARCH(-1)	1.0117	0.0000	0.0000	0.415	0.408
						0.430	0.403
						0.372	0.257

Fund: ISG*	GARCH(2,1)	sample ind					
: Z1	M10	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8722	C	-0.1090	0.3128	0.2709	0.006	0.006
s.e.	1.6424	ZHG	0.7780	0.0000	0.0000	0.018	0.013
AIC	3.7790	C	0.0892	0.0000	0.2160	0.026	0.025
SBC	3.8746	RESID(-1)^2	-0.0665	0.0000	0.1964	0.048	0.055
J-Bera	0.1394	GARCH(-1)	0.1147	0.0000	0.4168	0.041	0.047
		GARCH(-2)	0.9066	0.0000	0.0000	0.072	0.065
						0.103	0.107
						0.148	0.141

GARCH(2,1)+tsq
M11

Errors generated – model rejected

Fund: ISG*	GARCH(2,1)+tdm	sample ind					
: Z1	M12	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8752	C	0.2318	0.1384	0.1079	0.029	0.030
s.e.	1.6271	ZHG	0.8323	0.0000	0.0000	0.092	0.095
AIC	3.7450	ZHG*ZHG_TM	-0.1486	0.0012	0.0363	0.072	0.077
SBC	3.8566	C	0.1203	0.0000	0.1348	0.110	0.147
J-Bera	0.9460	RESID(-1)^2	-0.0707	0.0033	0.1880	0.122	0.155
		GARCH(-1)	0.4728	0.0000	0.6192	0.192	0.214
		GARCH(-2)	0.5402	0.0000	0.5730	0.181	0.206
						0.190	0.145

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	GARCH(1,2)	sample ind					
: Z1	M13	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8721	C	-0.0054	0.9572	0.9540	0.661	0.664
s.e.	1.6430	ZHG	0.7687	0.0000	0.0000	0.858	0.859
AIC	3.7376	C	0.0601	0.0000	0.1036	0.663	0.680
SBC	3.8332	RESID(-1)^2	0.0350	0.0029	0.6063	0.738	0.739
J-Bera	0.6421	RESID(-2)^2	-0.0782	0.0000	0.2096	0.565	0.585
		GARCH(-1)	1.0171	0.0000	0.0000	0.690	0.715
						0.685	0.678
						0.705	0.666

Fund: ISG*	GARCH(1,2)+tsq	sample ind					
: Z1	M14	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8777	C	0.1223	0.2981	0.1992	0.352	0.356
s.e.	1.6107	ZHG	0.7510	0.0000	0.0000	0.644	0.637
AIC	3.7060	ZHG^2	-0.0058	0.0000	0.0575	0.396	0.399
SBC	3.8175	C	0.0874	0.0000	0.0396	0.495	0.458
J-Bera	0.6571	RESID(-1)^2	0.0359	0.0000	0.6137	0.318	0.350
		RESID(-2)^2	-0.0991	0.0000	0.1182	0.434	0.488
		GARCH(-1)	1.0251	0.0000	0.0000	0.309	0.342
						0.253	0.273

Fund: ISG*	GARCH(1,2)+tdm	sample ind					
: Z1	M15	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8752	C	0.2385	0.0900	0.0943	0.337	0.341
s.e.	1.6268	ZHG	0.8289	0.0000	0.0000	0.599	0.609
AIC	3.7173	ZHG*ZHG_TM	-0.1412	0.0000	0.0524	0.370	0.402
SBC	3.8288	C	0.0730	0.0000	0.0158	0.458	0.449
J-Bera	0.9882	RESID(-1)^2	0.0398	0.1805	0.5764	0.381	0.410
		RESID(-2)^2	-0.0931	0.0000	0.1400	0.505	0.554
		GARCH(-1)	1.0209	0.0000	0.0000	0.404	0.390
						0.377	0.365

Fund: ISG*	GARCH(2,2)	sample ind					
: Z1	M16	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8722	C	-0.0498	0.6115	0.5745	0.827	0.828
s.e.	1.6462	ZHG	0.7712	0.0000	0.0000	0.409	0.418
AIC	3.7448	C	0.0683	0.0002	0.4639	0.356	0.370
SBC	3.8563	RESID(-1)^2	0.0109	0.0243	0.8754	0.400	0.381
J-Bera	0.7485	RESID(-2)^2	-0.0756	0.0000	0.2333	0.354	0.310
		GARCH(-1)	0.7031	0.0000	0.6027	0.476	0.434
		GARCH(-2)	0.3326	0.0000	0.8120	0.485	0.358
						0.505	0.355

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	GARCH(2,2)+tsq	sample ind					
: Z1	M17	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8776	C	0.1174	0.3325	0.2136	0.336	0.341
s.e.	1.6156	ZHG	0.7475	0.0000	0.0000	0.603	0.590
AIC	3.7139	ZHG^2	-0.0059	0.0000	0.0533	0.352	0.343
SBC	3.8414	C	0.0751	0.0000	0.0569	0.456	0.406
J-Bera	0.6876	RESID(-1)^2	0.0347	0.0000	0.6219	0.282	0.310
		RESID(-2)^2	-0.0921	0.0000	0.1990	0.392	0.444
		GARCH(-1)	1.1416	0.0000	0.0018	0.272	0.314
		GARCH(-2)	-0.1170	0.0000	0.7633	0.233	0.260

Fund: ISG*	GARCH(2,2)+tdm	sample ind					
: Z1	M18	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8753	C	0.2570	0.0641	0.0757	0.347	0.351
s.e.	1.6304	ZHG	0.8296	0.0000	0.0000	0.565	0.582
AIC	3.7315	ZHG*ZHG_TM	-0.1394	0.0007	0.0582	0.368	0.411
SBC	3.8590	C	0.0822	0.0000	0.0886	0.451	0.451
J-Bera	0.9804	RESID(-1)^2	0.0462	0.2636	0.5242	0.389	0.417
		RESID(-2)^2	-0.1022	0.0000	0.1178	0.514	0.562
		GARCH(-1)	0.9232	0.0000	0.0598	0.428	0.405
		GARCH(-2)	0.0962	0.2816	0.8484	0.398	0.376

Fund: ISG*	T1ARCH(1)	sample ind					
: Z1	M19	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8724	C	-0.0296	0.7961	0.7901	0.580	0.583
s.e.	1.6368	ZHG	0.7935	0.0000	0.0000	0.817	0.825
AIC	3.8229	C	2.2957	0.0000	0.0000	0.823	0.810
SBC	3.9026	RESID(-1)^2	0.1696	0.1059	0.4060	0.897	0.912
J-Bera	0.0000	RESID(-1)^2*(RESID(-1)<0)	-0.1091	0.4185	0.5808	0.874	0.893
						0.838	0.872
						0.906	0.933
						0.948	0.961

Fund: ISG*	T1ARCH(1)+tsq	sample ind					
: Z1	M20	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8780	C	0.1331	0.2959	0.3191	0.633	0.636
s.e.	1.6050	ZHG	0.7628	0.0000	0.0000	0.776	0.783
AIC	3.7902	ZHG^2	-0.0058	0.0000	0.1661	0.429	0.405
SBC	3.8859	C	2.1903	0.0000	0.0000	0.546	0.571
J-Bera	0.7785	RESID(-1)^2	0.1174	0.2399	0.3490	0.518	0.544
		RESID(-1)^2*(RESID(-1)<0)	-0.0056	0.9680	0.9725	0.548	0.613
						0.657	0.714
						0.645	0.653

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH(1)+tdm	sample ind					
: Z1	M21	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	C	0.2526	0.1337	0.1899	0.509	0.513
s.e.	1.6199	ZHG	0.8513	0.0000	0.0000	0.689	0.702
AIC	3.8058	ZHG*ZHG_TM	-0.1439	0.0026	0.1665	0.502	0.479
SBC	3.9014	C	2.2353	0.0000	0.0000	0.660	0.692
J-Bera	0.0837	RESID(-1)^2	0.1377	0.1923	0.3460	0.626	0.667
		RESID(-1)^2*(RESID(-1)<0)	-0.0547	0.6884	0.7366	0.615	0.700
						0.725	0.799
						0.790	0.834

Fund: ISG*	T1ARCH(1,1)	sample ind					
: Z1	M22	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8719	C	-0.0376	0.7153	0.7223	0.200	0.203
s.e.	1.6445	ZHG	0.7636	0.0000	0.0000	0.386	0.421
AIC	3.7321	C	0.0575	0.0000	0.2113	0.316	0.310
SBC	3.8277	RESID(-1)^2	-0.0539	0.0000	0.0319	0.398	0.435
J-Bera	0.7244	RESID(-1)^2*(RESID(-1)<0)	0.0044	0.4434	0.8599	0.355	0.347
		GARCH(-1)	1.0277	0.0000	0.0000	0.477	0.458
						0.490	0.443
						0.520	0.399

Fund: ISG*	T1ARCH(1,1)+tsq	sample ind					
: Z1	M23	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8778	C	0.1041	0.3425	0.3445	0.280	0.284
s.e.	1.6100	ZHG	0.7553	0.0000	0.0000	0.557	0.571
AIC	3.7054	ZHG^2	-0.0060	0.0000	0.0279	0.291	0.301
SBC	3.8170	C	0.0844	0.0000	0.0670	0.410	0.459
J-Bera	0.7519	RESID(-1)^2	-0.0715	0.0000	0.0075	0.302	0.345
		RESID(-1)^2*(RESID(-1)<0)	0.0034	0.7972	0.9104	0.411	0.469
		GARCH(-1)	1.0329	0.0000	0.0000	0.361	0.395
						0.259	0.187

Fund: ISG*	T1ARCH(1,1)+tdm	sample ind					
: Z1	M24	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8751	C	0.2515	0.0716	0.0895	0.167	0.171
s.e.	1.6278	ZHG	0.8350	0.0000	0.0000	0.359	0.387
AIC	3.7302	ZHG*ZHG_TM	-0.1580	0.0004	0.0255	0.230	0.228
SBC	3.8418	C	0.0855	0.0003	0.0084	0.316	0.359
J-Bera	0.9787	RESID(-1)^2	-0.0482	0.0072	0.0372	0.298	0.318
		RESID(-1)^2*(RESID(-1)<0)	-0.0093	0.5700	0.6710	0.414	0.421
		GARCH(-1)	1.0129	0.0000	0.0000	0.355	0.337
						0.341	0.238

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH(2,1)	sample ind					
: Z1	M25	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8722	C	-0.0981	0.3221	0.3669	0.020	0.021
s.e.	1.6464	ZHG	0.7752	0.0000	0.0000	0.057	0.046
AIC	3.7738	C	0.0848	0.0778	0.1488	0.087	0.086
SBC	3.8854	RESID(-1)^2	-0.1025	0.0065	0.0065	0.128	0.148
J-Bera	0.0821	RESID(-1)^2*(RESID(-1)<0)	0.0400	0.2411	0.3617	0.081	0.082
		GARCH(-1)	0.0932	0.1282	0.1373	0.130	0.101
		GARCH(-2)	0.9472	0.0000	0.0000	0.183	0.162
						0.257	0.228

Fund: ISG*	T1ARCH(2,1)+tsq	sample ind					
: Z1	M26	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8776	C	0.0592	0.6593	0.5926	0.046	0.048
s.e.	1.6152	ZHG	0.7609	0.0000	0.0000	0.109	0.093
AIC	3.7527	ZHG^2	-0.0060	0.0001	0.0241	0.107	0.118
SBC	3.8802	C	0.1492	0.0053	0.0072	0.140	0.193
J-Bera	0.9208	RESID(-1)^2	-0.1007	0.0000	0.0075	0.098	0.128
		RESID(-1)^2*(RESID(-1)<0)	0.0245	0.4305	0.5686	0.155	0.160
		GARCH(-1)	0.1177	0.0000	0.2073	0.175	0.211
		GARCH(-2)	0.9005	0.0000	0.0000	0.205	0.201

Fund: ISG*	T1ARCH(2,1)+tdm	sample ind					
: Z1	M27	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8743	C	0.2820	0.1111	0.0504	0.026	0.027
s.e.	1.6366	ZHG	0.8426	0.0000	0.0000	0.084	0.088
AIC	3.7462	ZHG*ZHG_TM	-0.1873	0.0001	0.0049	0.062	0.067
SBC	3.8737	C	0.1172	0.0248	0.2564	0.100	0.133
J-Bera	0.9668	RESID(-1)^2	-0.0802	0.0035	0.0916	0.112	0.143
		RESID(-1)^2*(RESID(-1)<0)	-0.0057	0.7805	0.9049	0.177	0.202
		GARCH(-1)	0.5258	0.0000	0.5760	0.159	0.180
		GARCH(-2)	0.5012	0.0000	0.5947	0.164	0.118

Fund: ISG*	T1ARCH(1,2)	sample ind					
: Z1	M28	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8721	C	-0.0269	0.7920	0.8010	0.676	0.679
s.e.	1.6470	ZHG	0.7681	0.0000	0.0000	0.824	0.828
AIC	3.7356	C	0.0610	0.0000	0.2029	0.649	0.668
SBC	3.8471	RESID(-1)^2	0.0159	0.2824	0.8093	0.685	0.683
J-Bera	0.7163	RESID(-1)^2*(RESID(-1)<0)	0.0062	0.5027	0.8151	0.539	0.555
		RESID(-2)^2	-0.0689	0.0000	0.2463	0.667	0.688
		GARCH(-1)	1.0250	0.0000	0.0000	0.647	0.621
						0.664	0.614

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH(1,2)+tsq	sample ind					
: Z1	M29	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8776	C	0.1155	0.3439	0.3079	0.400	0.404
s.e.	1.6154	ZHG	0.7474	0.0000	0.0000	0.693	0.686
AIC	3.7147	ZHG^2	-0.0061	0.0000	0.0466	0.421	0.423
SBC	3.8422	C	0.0903	0.0000	0.0485	0.526	0.493
J-Bera	0.6184	RESID(-1)^2	0.0287	0.2849	0.6886	0.334	0.368
		RESID(-1)^2*(RESID(-1)<0)	-0.0028	0.9179	0.9143	0.449	0.506
		RESID(-2)^2	-0.0922	0.0033	0.1445	0.309	0.348
		GARCH(-1)	1.0251	0.0000	0.0000	0.254	0.276

Fund: ISG*	T1ARCH(1,2)+tdm	sample ind					
: Z1	M30	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8751	C	0.2674	0.0842	0.0757	0.342	0.346
s.e.	1.6314	ZHG	0.8373	0.0000	0.0000	0.630	0.634
AIC	3.7252	ZHG*ZHG_TM	-0.1611	0.0001	0.0258	0.375	0.395
SBC	3.8527	C	0.0750	0.0503	0.0777	0.510	0.504
J-Bera	0.9011	RESID(-1)^2	0.0503	0.5573	0.4892	0.383	0.410
		RESID(-1)^2*(RESID(-1)<0)	-0.0184	0.4790	0.4701	0.508	0.559
		RESID(-2)^2	-0.0974	0.2238	0.1325	0.392	0.407
		GARCH(-1)	1.0218	0.0000	0.0000	0.387	0.391

Fund: ISG*	T1ARCH(2,2)	sample ind					
: Z1	M31	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8722	C	-0.0272	0.7890	0.7974	0.798	0.799
s.e.	1.6504	ZHG	0.7703	0.0000	0.0000	0.715	0.720
AIC	3.7472	C	0.0692	0.0000	0.4157	0.562	0.578
SBC	3.8748	RESID(-1)^2	-0.0006	0.9751	0.9921	0.603	0.599
J-Bera	0.7608	RESID(-1)^2*(RESID(-1)<0)	0.0077	0.0001	0.7986	0.489	0.476
		RESID(-2)^2	-0.0611	0.0081	0.4081	0.616	0.612
		GARCH(-1)	0.8840	0.0000	0.5015	0.604	0.533
		GARCH(-2)	0.1459	0.0000	0.9145	0.612	0.510

Fund: ISG*	T1ARCH(2,2)+tsq	sample ind					
: Z1	M32	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8776	C	0.1244	0.3041	0.2698	0.439	0.443
s.e.	1.6196	ZHG	0.7461	0.0000	0.0000	0.740	0.735
AIC	3.7251	ZHG^2	-0.0064	0.0000	0.0338	0.460	0.468
SBC	3.8685	C	0.1025	0.0002	0.0474	0.561	0.538
J-Bera	0.5847	RESID(-1)^2	0.0192	0.5659	0.7842	0.369	0.405
		RESID(-1)^2*(RESID(-1)<0)	-0.0016	0.9376	0.9535	0.487	0.545
		RESID(-2)^2	-0.0887	0.0000	0.1818	0.335	0.368
		GARCH(-1)	0.9500	0.0000	0.0303	0.265	0.283
		GARCH(-2)	0.0753	0.0000	0.8697		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH(2,2)+tdm	sample ind					
: Z1	M33	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8754	C	0.2798	0.0584	0.0727	0.653	0.656
s.e.	1.6340	ZHG	0.8361	0.0000	0.0000	0.708	0.717
AIC	3.7527	ZHG*ZHG_TM	-0.1506	0.0017	0.0461	0.460	0.490
SBC	3.8962	C	0.1161	0.0127	0.1344	0.584	0.597
J-Bera	0.8924	RESID(-1)^2	0.0450	0.0337	0.5306	0.479	0.485
		RESID(-1)^2*(RESID(-1)<0)	-0.0192	0.5612	0.5138	0.608	0.629
		RESID(-2)^2	-0.0949	0.0000	0.1305	0.549	0.505
		GARCH(-1)	0.7605	0.0000	0.2170	0.522	0.451
		GARCH(-2)	0.2460	0.0000	0.6916		

Fund: ISG*	T2ARCH(1)	sample ind					
: Z1	M34	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0374	0.7483	0.7352	0.589	0.593
s.e.	1.6404	ZHG	0.7895	0.0000	0.0000	0.852	0.851
AIC	3.8296	C	2.2391	0.0000	0.0000	0.848	0.859
SBC	3.9252	RESID(-1)^2	0.1453	0.1435	0.4969	0.909	0.938
J-Bera	0.0000	RESID(-1)^2*(RESID(-1)<0)	-0.0831	0.5284	0.6885	0.877	0.904
		RESID(-2)^2*(RESID(-2)<0)	0.0606	0.7131	0.3025	0.839	0.883
						0.907	0.941

Fund: ISG*	T2ARCH(1)+tsq	sample ind					
: Z1	M35	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	C	0.1293	0.3095	0.3316	0.571	0.575
s.e.	1.6096	ZHG	0.7546	0.0000	0.0000	0.843	0.838
AIC	3.7925	ZHG^2	-0.0061	0.0000	0.1408	0.513	0.533
SBC	3.9041	C	2.0915	0.0000	0.0000	0.609	0.681
J-Bera	0.6952	RESID(-1)^2	0.0648	0.5137	0.5571	0.583	0.605
		RESID(-1)^2*(RESID(-1)<0)	0.0595	0.6792	0.7023	0.622	0.680
		RESID(-2)^2*(RESID(-2)<0)	0.1290	0.4579	0.2126	0.726	0.786

Fund: ISG*	T2ARCH(1)+tdm	sample ind					
: Z1	M36	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	C	0.2535	0.1277	0.1936	0.488	0.492
s.e.	1.6239	ZHG	0.8490	0.0000	0.0000	0.786	0.783
AIC	3.8101	ZHG*ZHG_TM	-0.1502	0.0016	0.1515	0.588	0.605
SBC	3.9217	C	2.1589	0.0000	0.0000	0.730	0.801
J-Bera	0.0312	RESID(-1)^2	0.0953	0.3468	0.5043	0.670	0.726
		RESID(-1)^2*(RESID(-1)<0)	-0.0080	0.9531	0.9606	0.652	0.748
		RESID(-2)^2*(RESID(-2)<0)	0.0982	0.5548	0.2434	0.758	0.845
						0.838	0.891

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH(1,1)	sample ind					
: Z1	M37	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8720	C	-0.0311	0.7555	0.7689	0.937	0.938
s.e.	1.6479	ZHG	0.7652	0.0000	0.0000	0.833	0.838
AIC	3.7409	C	0.0651	0.0000	0.0856	0.670	0.670
SBC	3.8525	RESID(-1)^2	-0.0503	0.0000	0.0303	0.714	0.716
J-Bera	0.6341	RESID(-1)^2*(RESID(-1)<0)	0.0582	0.2565	0.3298	0.588	0.578
		RESID(-2)^2*(RESID(-2)<0)	-0.0574	0.2445	0.2954	0.709	0.704
		GARCH(-1)	1.0220	0.0000	0.0000	0.681	0.626

Fund: ISG*	T2ARCH(1,1)+tsq	sample ind					
: Z1	M38	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8775	C	0.0923	0.4539	0.4138	0.891	0.892
s.e.	1.6161	ZHG	0.7477	0.0000	0.0000	0.986	0.987
AIC	3.7184	ZHG^2	-0.0059	0.0001	0.0491	0.615	0.624
SBC	3.8459	C	0.1016	0.0119	0.0091	0.694	0.716
J-Bera	0.7122	RESID(-1)^2	-0.0630	0.0055	0.0042	0.460	0.497
		RESID(-1)^2*(RESID(-1)<0)	0.0757	0.5005	0.4204	0.576	0.633
		RESID(-2)^2*(RESID(-2)<0)	-0.0844	0.4559	0.3617	0.435	0.447
		GARCH(-1)	1.0207	0.0000	0.0000	0.391	0.348

Fund: ISG*	T2ARCH(1,1)+tdm	sample ind					
: Z1	M39	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8752	C	0.2741	0.0469	0.0638	0.898	0.899
s.e.	1.6309	ZHG	0.8375	0.0000	0.0000	0.886	0.891
AIC	3.7352	ZHG*ZHG_TM	-0.1592	0.0001	0.0230	0.568	0.572
SBC	3.8627	C	0.0916	0.0000	0.0005	0.689	0.701
J-Bera	0.9560	RESID(-1)^2	-0.0478	0.0000	0.0380	0.545	0.548
		RESID(-1)^2*(RESID(-1)<0)	0.0430	0.0000	0.5881	0.670	0.678
		RESID(-2)^2*(RESID(-2)<0)	-0.0588	0.0001	0.4447	0.554	0.512
		GARCH(-1)	1.0133	0.0000	0.0000	0.537	0.442

Fund: ISG*	T2ARCH(2,1)	sample ind					
: Z1	M40	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8718	C	-0.0422	0.6956	0.6974	0.074	0.077
s.e.	1.6530	ZHG	0.7627	0.0000	0.0000	0.199	0.214
AIC	3.7742	C	0.1042	0.0019	0.2855	0.217	0.224
SBC	3.9017	RESID(-1)^2	-0.0743	0.0167	0.0344	0.296	0.345
J-Bera	0.4273	RESID(-1)^2*(RESID(-1)<0)	0.0235	0.2862	0.7013	0.272	0.290
		RESID(-2)^2*(RESID(-2)<0)	-0.0255	0.2239	0.6548	0.381	0.377
		GARCH(-1)	0.2954	0.0000	0.5998	0.404	0.405
		GARCH(-2)	0.7324	0.0000	0.1720	0.457	0.392

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH(2,1)+tsq	sample ind					
: Z1	M41	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8775	C	0.0991	0.4197	0.3819	0.798	0.800
s.e.	1.6199	ZHG	0.7477	0.0000	0.0000	0.966	0.964
AIC	3.7321	ZHG^2	-0.0065	0.0000	0.0260	0.660	0.671
SBC	3.8755	C	0.1095	0.0000	0.0967	0.757	0.762
J-Bera	0.6926	RESID(-1)^2	-0.0630	0.0000	0.1703	0.500	0.539
		RESID(-1)^2*(RESID(-1)<0)	0.1106	0.0836	0.2532	0.616	0.671
		RESID(-2)^2*(RESID(-2)<0)	-0.1196	0.0785	0.2199	0.434	0.460
		GARCH(-1)	1.0437	0.0000	0.0753	0.392	0.383
		GARCH(-2)	-0.0261	0.0000	0.9656		

Fund: ISG*	T2ARCH(2,1)+tdm	sample ind					
: Z1	M42	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8751	C	0.3228	0.0191	0.0245	0.666	0.669
s.e.	1.6356	ZHG	0.8390	0.0000	0.0000	0.812	0.816
AIC	3.7267	ZHG*ZHG_TM	-0.1642	0.0000	0.0144	0.523	0.548
SBC	3.8702	C	0.0749	0.0080	0.2449	0.686	0.706
J-Bera	0.8677	RESID(-1)^2	-0.0553	0.0004	0.3628	0.477	0.487
		RESID(-1)^2*(RESID(-1)<0)	0.0587	0.0744	0.4685	0.605	0.630
		RESID(-2)^2*(RESID(-2)<0)	-0.0747	0.0000	0.3777	0.522	0.507
		GARCH(-1)	1.0882	0.0000	0.1985	0.526	0.469
		GARCH(-2)	-0.0578	0.0000	0.9479		

Fund: ISG*	T2ARCH(1,2)	sample ind					
: Z1	M43	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8721	C	-0.0069	0.9444	0.9487	0.578	0.581
s.e.	1.6512	ZHG	0.7683	0.0000	0.0000	0.811	0.814
AIC	3.7451	C	0.0537	0.0006	0.3387	0.612	0.634
SBC	3.8726	RESID(-1)^2	0.0598	0.1772	0.6106	0.670	0.667
J-Bera	0.7838	RESID(-1)^2*(RESID(-1)<0)	-0.0427	0.7104	0.6994	0.497	0.521
		RESID(-2)^2	-0.1120	0.0388	0.2931	0.626	0.658
		RESID(-2)^2*(RESID(-2)<0)	0.0485	0.6993	0.6619	0.629	0.623
		GARCH(-1)	1.0284	0.0000	0.0000	0.645	0.610

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH(1,2)+tsq	sample ind					
: Z1	M44	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	C	0.1577	0.2149	0.2286	0.452	0.456
s.e.	1.6175	ZHG	0.7552	0.0000	0.0000	0.690	0.705
AIC	3.8018	ZHG^2	-0.0060	0.0000	0.1255	0.692	0.706
SBC	3.9453	C	2.7553	0.0318	0.0000	0.797	0.866
J-Bera	0.7343	RESID(-1)^2	0.0476	0.6044	0.5869	0.788	0.851
		RESID(-1)^2*(RESID(-1)<0)	0.0715	0.6040	0.5721	0.815	0.868
		RESID(-2)^2	-0.0725	0.4202	0.0241	0.889	0.928
		RESID(-2)^2*(RESID(-2)<0)	0.2625	0.1673	0.0020	0.928	0.944
		GARCH(-1)	-0.2378	0.6511	0.2502		

Fund: ISG*	T2ARCH(1,2)+tdm	sample ind					
: Z1	M45	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8750	C	0.2839	0.0587	0.0607	0.389	0.393
s.e.	1.6365	ZHG	0.8373	0.0000	0.0000	0.678	0.683
AIC	3.7413	ZHG*ZHG_TM	-0.1664	0.0002	0.0207	0.408	0.431
SBC	3.8848	C	0.0843	0.0000	0.0144	0.546	0.546
J-Bera	0.9276	RESID(-1)^2	0.0424	0.0000	0.6465	0.417	0.446
		RESID(-1)^2*(RESID(-1)<0)	-0.0140	0.8965	0.8930	0.544	0.594
		RESID(-2)^2	-0.0878	0.0000	0.2979	0.421	0.432
		RESID(-2)^2*(RESID(-2)<0)	-0.0015	0.9897	0.9888	0.412	0.410
		GARCH(-1)	1.0144	0.0000	0.0000		

Fund: ISG*	T2ARCH(2,2)	sample ind					
: Z1	M46	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8721	C	0.0363	0.7187	0.7397	0.950	0.950
s.e.	1.6551	ZHG	0.7742	0.0000	0.0000	0.542	0.550
AIC	3.7767	C	0.1015	0.0786	0.4041	0.510	0.510
SBC	3.9202	RESID(-1)^2	0.0961	0.3235	0.4727	0.598	0.580
J-Bera	0.6444	RESID(-1)^2*(RESID(-1)<0)	-0.0896	0.3251	0.5011	0.599	0.561
		RESID(-2)^2	-0.1724	0.0417	0.1195	0.719	0.687
		RESID(-2)^2*(RESID(-2)<0)	0.1202	0.1485	0.3545	0.768	0.701
		GARCH(-1)	0.6207	0.0875	0.0891	0.782	0.705
		GARCH(-2)	0.3982	0.2677	0.3012		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH(2,2)+tsq	sample ind					
: Z1	M47	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8774	C	0.1142	0.3771	0.2619	0.757	0.759
s.e.	1.6248	ZHG	0.7744	0.0000	0.0000	0.948	0.950
AIC	3.7880	ZHG^2	-0.0042	0.0038	0.0771	0.991	0.995
SBC	3.9474	C	3.8480	0.0041	0.0000	0.998	1.000
J-Bera	0.5657	RESID(-1)^2	0.1400	0.1732	0.1475	0.998	0.998
		RESID(-1)^2*(RESID(-1)<0)	-0.0071	0.9612	0.9575	0.997	0.998
		RESID(-2)^2	0.0025	0.9839	0.9738	0.999	0.999
		RESID(-2)^2*(RESID(-2)<0)	0.1988	0.2573	0.0363	0.999	0.999
		GARCH(-1)	-0.3784	0.2830	0.0263		
		GARCH(-2)	-0.3788	0.1845	0.0030		

Fund: ISG*	T2ARCH(2,2)+tdm	sample ind					
: Z1	M48	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8751	C	0.2673	0.0696	0.0730	0.652	0.654
s.e.	1.6396	ZHG	0.8244	0.0000	0.0000	0.805	0.810
AIC	3.7439	ZHG*ZHG_TM	-0.1308	0.0000	0.0675	0.445	0.471
SBC	3.9033	C	0.0819	0.2542	0.2213	0.571	0.583
J-Bera	0.9091	RESID(-1)^2	0.0650	0.5260	0.5460	0.428	0.440
		RESID(-1)^2*(RESID(-1)<0)	-0.0705	0.4985	0.5339	0.556	0.583
		RESID(-2)^2	-0.1249	0.2412	0.1542	0.514	0.490
		RESID(-2)^2*(RESID(-2)<0)	0.0572	0.5854	0.6207	0.493	0.428
		GARCH(-1)	0.7907	0.2449	0.0723		
		GARCH(-2)	0.2402	0.7285	0.5964		

Fund: ISG*	E1GARCH(1)	sample ind					
: Z1	M49	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0268	0.8131	0.8165	0.373	0.377
s.e.	1.6364	ZHG	0.7897	0.0000	0.0000	0.573	0.595
AIC	3.8313	C(3)	0.7844	0.0000	0.0018	0.649	0.631
SBC	3.9110	C(4)	0.2092	0.0928	0.3914	0.780	0.805
J-Bera	0.0000	C(5)	0.0740	0.3775	0.5282	0.768	0.796
						0.764	0.815
						0.851	0.893
						0.909	0.935

Fund: ISG*	E1GARCH(1)+tsq	sample ind					
: Z1	M50	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8780	C	0.1465	0.2608	0.2697	0.307	0.311
s.e.	1.6050	ZHG	0.7626	0.0000	0.0000	0.434	0.462
AIC	3.7995	ZHG^2	-0.0058	0.0000	0.1719	0.261	0.232
SBC	3.8951	C(4)	0.7423	0.0000	0.0001	0.377	0.417
J-Bera	0.7308	C(5)	0.2061	0.0960	0.3399	0.344	0.403
		C(6)	0.0061	0.9415	0.9578	0.352	0.464
						0.462	0.568
						0.437	0.479

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E1GARCH(1)+tdm	sample ind					
: Z1	M51	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	C	0.2498	0.1469	0.1977	0.212	0.216
s.e.	1.6199	ZHG	0.8469	0.0000	0.0000	0.328	0.360
AIC	3.8166	ZHG*ZHG_TM	-0.1373	0.0040	0.2011	0.280	0.257
SBC	3.9122	C(4)	0.7650	0.0000	0.0006	0.425	0.465
J-Bera	0.0653	C(5)	0.2014	0.0787	0.3914	0.397	0.458
		C(6)	0.0460	0.5771	0.6955	0.393	0.515
						0.508	0.629
						0.582	0.678

Fund: ISG*	E1GARCH(1,1)	sample ind					
: Z1	M52	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0159	0.8889	0.8906	0.288	0.292
s.e.	1.6406	ZHG	0.7898	0.0000	0.0000	0.436	0.467
AIC	3.8390	C(3)	1.0357	0.1590	0.0886	0.530	0.508
SBC	3.9347	C(4)	0.1956	0.1109	0.4092	0.675	0.705
J-Bera	0.0000	C(5)	0.0862	0.2718	0.4261	0.679	0.713
		C(6)	-0.2566	0.7224	0.5893	0.683	0.745
						0.784	0.840
						0.858	0.897

Fund: ISG*	E1GARCH(1,1)+tsq	sample ind					
: Z1	M53	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	C	0.1168	0.3271	0.3482	0.262	0.267
s.e.	1.6093	ZHG	0.7596	0.0000	0.0000	0.534	0.546
AIC	3.7446	ZHG^2	-0.0058	0.0000	0.1066	0.293	0.301
SBC	3.8562	C(4)	0.1013	0.0000	0.0293	0.346	0.417
J-Bera	0.9096	C(5)	-0.0990	0.0000	0.0673	0.313	0.376
		C(6)	-0.0129	0.5471	0.5259	0.431	0.496
		C(7)	0.9679	0.0000	0.0000	0.386	0.415
						0.290	0.227

Fund: ISG*	E1GARCH(1,1)+tdm	sample ind					
: Z1	M54	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	C	0.2475	0.1519	0.1986	0.161	0.165
s.e.	1.6240	ZHG	0.8459	0.0000	0.0000	0.250	0.285
AIC	3.8258	ZHG*ZHG_TM	-0.1338	0.0064	0.2080	0.219	0.199
SBC	3.9374	C(4)	0.8961	0.2590	0.1337	0.348	0.389
J-Bera	0.0736	C(5)	0.1930	0.0998	0.4153	0.326	0.387
		C(6)	0.0591	0.4506	0.6136	0.324	0.447
		C(7)	-0.1354	0.8676	0.8025	0.432	0.563
						0.503	0.611

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E1GARCH(2,1)	sample ind					
: Z1	M55	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8718	C	0.0801	0.5037	0.4628	0.097	0.100
s.e.	1.6492	ZHG	0.7922	0.0000	0.0000	0.067	0.093
AIC	3.8226	C(3)	2.2394	0.0000	0.0000	0.095	0.089
SBC	3.9342	C(4)	0.1064	0.3550	0.3770	0.147	0.163
J-Bera	0.2911	C(5)	0.0404	0.3354	0.3837	0.059	0.055
		C(6)	-0.5878	0.0000	0.0000	0.084	0.084
		C(7)	-0.9131	0.0000	0.0000	0.127	0.088
						0.171	0.116

Fund: ISG*	E1GARCH(2,1)+tsq	sample ind					
: Z1	M56	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8776	C	0.0831	0.4998	0.4993	0.385	0.389
s.e.	1.6150	ZHG	0.7557	0.0000	0.0000	0.612	0.612
AIC	3.7886	ZHG^2	-0.0053	0.0000	0.1637	0.805	0.890
SBC	3.9161	C(4)	1.0268	0.0001	0.0000	0.899	0.948
J-Bera	0.8319	C(5)	0.3433	0.0057	0.0115	0.957	0.985
		C(6)	-0.0833	0.2565	0.2501	0.979	0.996
		C(7)	0.3419	0.0004	0.0004	0.986	0.996
		C(8)	-0.7861	0.0000	0.0000	0.907	0.950

Fund: ISG*	E1GARCH(2,1)+tdm	sample ind					
: Z1	M57	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8754	C	0.2030	0.2161	0.2526	0.292	0.296
s.e.	1.6296	ZHG	0.8309	0.0000	0.0000	0.432	0.443
AIC	3.8029	ZHG*ZHG_TM	-0.1333	0.0053	0.1543	0.624	0.737
SBC	3.9304	C(4)	1.0944	0.0000	0.0000	0.747	0.838
J-Bera	0.1883	C(5)	0.3057	0.0112	0.0298	0.857	0.950
		C(6)	-0.0780	0.2562	0.2743	0.905	0.980
		C(7)	0.3559	0.0000	0.0003	0.905	0.970
		C(8)	-0.8187	0.0000	0.0000	0.862	0.951

Fund: ISG*	E1GARCH(1,2)	sample ind					
: Z1	M58	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0205	0.8630	0.8584	0.373	0.377
s.e.	1.6444	ZHG	0.7880	0.0000	0.0000	0.603	0.624
AIC	3.8480	C(3)	1.0328	0.1904	0.1339	0.679	0.664
SBC	3.9596	C(4)	0.2107	0.1189	0.3842	0.802	0.831
J-Bera	0.0000	C(5)	0.0591	0.7979	0.8330	0.786	0.817
		C(6)	0.0821	0.3122	0.4706	0.769	0.822
		C(7)	-0.3149	0.7192	0.7162	0.854	0.899
						0.913	0.940

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E1GARCH(1,2)+tsq	sample ind					
: Z1	M59	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	C	0.1495	0.2538	0.2572	0.417	0.421
s.e.	1.6132	ZHG	0.7585	0.0000	0.0000	0.717	0.722
AIC	3.8152	ZHG^2	-0.0058	0.0000	0.1816	0.446	0.446
SBC	3.9427	C(4)	0.9014	0.1689	0.2105	0.562	0.640
J-Bera	0.6902	C(5)	0.2341	0.0858	0.2686	0.461	0.518
		C(6)	0.2013	0.4655	0.2193	0.470	0.580
		C(7)	0.0266	0.7359	0.7706	0.582	0.694
		C(8)	-0.3790	0.6474	0.6267	0.618	0.662

Fund: ISG*	E1GARCH(1,2)+tdm	sample ind					
: Z1	M60	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	C	0.2658	0.1165	0.1801	0.289	0.294
s.e.	1.6280	ZHG	0.8454	0.0000	0.0000	0.557	0.570
AIC	3.8321	ZHG*ZHG_TM	-0.1443	0.0022	0.1909	0.462	0.460
SBC	3.9596	C(4)	0.9629	0.1464	0.1890	0.621	0.693
J-Bera	0.0307	C(5)	0.2198	0.0872	0.3348	0.538	0.615
		C(6)	0.1703	0.4933	0.3534	0.510	0.644
		C(7)	0.0531	0.5012	0.5818	0.627	0.756
		C(8)	-0.3781	0.6244	0.6311	0.715	0.805

Fund: ISG*	E1GARCH(2,2)	sample ind					
: Z1	M61	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8720	C	0.0027	0.9777	0.9734	0.304	0.308
s.e.	1.6520	ZHG	0.7663	0.0000	0.0000	0.587	0.595
AIC	3.7951	C(3)	1.5260	0.0001	0.0000	0.739	0.748
SBC	3.9226	C(4)	0.3288	0.0016	0.0077	0.829	0.877
J-Bera	0.0568	C(5)	0.3814	0.0033	0.0000	0.688	0.772
		C(6)	0.0409	0.2173	0.1926	0.769	0.851
		C(7)	-0.6081	0.0000	0.0000	0.828	0.890
		C(8)	-0.7844	0.0000	0.0000	0.882	0.937

Fund: ISG*	E1GARCH(2,2)+tsq	sample ind					
: Z1	M62	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8762	C	0.0877	0.4860	0.3983	0.280	0.284
s.e.	1.6283	ZHG	0.7667	0.0000	0.0000	0.551	0.562
AIC	3.8020	ZHG^2	-0.0028	0.1215	0.3780	0.675	0.686
SBC	3.9454	C(4)	1.5622	0.0002	0.0000	0.754	0.824
J-Bera	0.4035	C(5)	0.2969	0.0300	0.0351	0.611	0.722
		C(6)	0.3090	0.0378	0.0017	0.689	0.802
		C(7)	0.0209	0.7044	0.5781	0.759	0.844
		C(8)	-0.5871	0.0000	0.0000	0.840	0.914
		C(9)	-0.7430	0.0000	0.0000		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E1GARCH(2,2)+tdm	sample ind					
: Z1	M63	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8709	C	-0.0385	0.8122	0.7437	0.293	0.297
s.e.	1.6632	ZHG	0.7547	0.0000	0.0000	0.574	0.581
AIC	3.8041	ZHG*ZHG_TM	0.0197	0.7266	0.7043	0.743	0.752
SBC	3.9475	C(4)	1.5045	0.0002	0.0000	0.842	0.884
J-Bera	0.0390	C(5)	0.3343	0.0019	0.0053	0.712	0.793
		C(6)	0.4096	0.0013	0.0000	0.788	0.867
		C(7)	0.0412	0.1851	0.1253	0.842	0.901
		C(8)	-0.6129	0.0000	0.0000	0.887	0.940
		C(9)	-0.7914	0.0000	0.0000		

Fund: ISG*	E2GARCH(1)	sample ind					
: Z1	M64	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0159	0.8906	0.8887	0.508	0.512
s.e.	1.6407	ZHG	0.7791	0.0000	0.0000	0.794	0.799
AIC	3.8332	C(3)	0.7805	0.0000	0.0018	0.867	0.866
SBC	3.9288	C(4)	0.2034	0.1353	0.3866	0.929	0.953
J-Bera	0.0000	C(5)	0.0310	0.7402	0.7944	0.893	0.919
		C(6)	-0.1325	0.2638	0.1771	0.881	0.914
						0.935	0.959
						0.966	0.978

Fund: ISG*	E2GARCH(1)+tsq	sample ind					
: Z1	M65	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8778	C	0.1543	0.2287	0.2464	0.394	0.398
s.e.	1.6101	ZHG	0.7521	0.0000	0.0000	0.532	0.554
AIC	3.7992	ZHG^2	-0.0060	0.0000	0.1556	0.415	0.383
SBC	3.9108	C(4)	0.7312	0.0000	0.0001	0.543	0.600
J-Bera	0.7513	C(5)	0.2060	0.1304	0.2932	0.551	0.643
		C(6)	-0.0597	0.5440	0.5695	0.574	0.680
		C(7)	-0.1480	0.1815	0.1101	0.688	0.780
						0.745	0.802

Fund: ISG*	E2GARCH(1)+tdm	sample ind					
: Z1	M66	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	C	0.2510	0.1393	0.1935	0.322	0.327
s.e.	1.6244	ZHG	0.8371	0.0000	0.0000	0.515	0.538
AIC	3.8182	ZHG*ZHG_TM	-0.1358	0.0047	0.1977	0.503	0.487
SBC	3.9297	C(4)	0.7636	0.0000	0.0004	0.663	0.733
J-Bera	0.0298	C(5)	0.1918	0.1279	0.3695	0.622	0.708
		C(6)	-0.0079	0.9346	0.9427	0.605	0.723
		C(7)	-0.1323	0.2407	0.1606	0.717	0.821
						0.804	0.875

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E2GARCH(1,1)	sample ind					
: Z1	M67	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8724	C	-0.0164	0.8879	0.8846	0.509	0.513
s.e.	1.6449	ZHG	0.7776	0.0000	0.0000	0.803	0.806
AIC	3.8425	C(3)	0.7102	0.2255	0.0918	0.871	0.874
SBC	3.9541	C(4)	0.2008	0.1654	0.3917	0.929	0.955
J-Bera	0.0000	C(5)	0.0260	0.7848	0.8258	0.887	0.915
		C(6)	-0.1468	0.2160	0.1890	0.876	0.911
		C(7)	0.0768	0.8914	0.8827	0.932	0.957
						0.963	0.976

Fund: ISG*	E2GARCH(1,1)+tsq	sample ind					
: Z1	M68	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8778	C	0.1537	0.2349	0.2483	0.400	0.405
s.e.	1.6141	ZHG	0.7520	0.0000	0.0000	0.544	0.565
AIC	3.8087	ZHG^2	-0.0060	0.0000	0.1565	0.422	0.391
SBC	3.9362	C(4)	0.7178	0.2312	0.0708	0.550	0.607
J-Bera	0.7511	C(5)	0.2069	0.1347	0.2883	0.557	0.646
		C(6)	-0.0602	0.5427	0.5676	0.580	0.683
		C(7)	-0.1479	0.1889	0.1093	0.693	0.783
		C(8)	0.0142	0.9822	0.9732	0.751	0.806

Fund: ISG*	E2GARCH(1,1)+tdm	sample ind					
: Z1	M69	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	C	0.2501	0.1451	0.1944	0.332	0.336
s.e.	1.6285	ZHG	0.8367	0.0000	0.0000	0.537	0.558
AIC	3.8276	ZHG*ZHG_TM	-0.1357	0.0061	0.1977	0.518	0.503
SBC	3.9552	C(4)	0.7331	0.2503	0.0818	0.676	0.748
J-Bera	0.0296	C(5)	0.1925	0.1353	0.3642	0.632	0.716
		C(6)	-0.0094	0.9228	0.9320	0.615	0.730
		C(7)	-0.1346	0.2340	0.1654	0.726	0.827
		C(8)	0.0326	0.9607	0.9442	0.812	0.880

Fund: ISG*	E2GARCH(2,1)	sample ind					
: Z1	M70	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8710	C	-0.0528	0.6305	0.6029	0.254	0.258
s.e.	1.6582	ZHG	0.7527	0.0000	0.0000	0.446	0.449
AIC	3.7976	C(3)	1.3086	0.0000	0.0000	0.566	0.645
SBC	3.9251	C(4)	0.2918	0.0231	0.0009	0.712	0.802
J-Bera	0.0608	C(5)	-0.0102	0.8794	0.8832	0.821	0.931
		C(6)	-0.1847	0.0038	0.0883	0.894	0.982
		C(7)	0.2270	0.0002	0.0000	0.899	0.976
		C(8)	-0.8830	0.0000	0.0000	0.926	0.984

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E2GARCH(2,1)+tsq	sample ind					
: Z1	M71	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8767	C	0.0692	0.5534	0.5626	0.458	0.462
s.e.	1.6252	ZHG	0.7482	0.0000	0.0000	0.615	0.621
AIC	3.7821	ZHG^2	-0.0042	0.0026	0.2320	0.786	0.855
SBC	3.9256	C(4)	1.1150	0.0000	0.0000	0.900	0.952
J-Bera	0.8420	C(5)	0.3561	0.0068	0.0011	0.956	0.997
		C(6)	-0.0381	0.6253	0.6114	0.980	0.999
		C(7)	-0.1571	0.1095	0.0718	0.984	0.999
		C(8)	0.2356	0.0280	0.0000	0.959	0.989
		C(9)	-0.8084	0.0000	0.0000		

Fund: ISG*	E2GARCH(2,1)+tdm	sample ind					
: Z1	M72	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8744	C	0.1447	0.3549	0.3621	0.351	0.355
s.e.	1.6404	ZHG	0.8012	0.0000	0.0000	0.474	0.486
AIC	3.7898	ZHG*ZHG_TM	-0.0964	0.0512	0.2312	0.633	0.728
SBC	3.9333	C(4)	1.2047	0.0000	0.0000	0.779	0.876
J-Bera	0.4247	C(5)	0.3244	0.0103	0.0007	0.875	0.980
		C(6)	-0.0313	0.6703	0.6657	0.931	0.995
		C(7)	-0.1781	0.0266	0.0737	0.928	0.988
		C(8)	0.2286	0.0063	0.0000	0.926	0.985
		C(9)	-0.8441	0.0000	0.0000		

Fund: ISG*	E2GARCH(1,2)	sample ind					
: Z1	M73	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8724	C	-0.0049	0.9665	0.9655	0.471	0.475
s.e.	1.6491	ZHG	0.7785	0.0000	0.0000	0.707	0.721
AIC	3.8502	C(3)	0.6862	0.2500	0.0807	0.826	0.815
SBC	3.9778	C(4)	0.1958	0.1733	0.3919	0.907	0.931
J-Bera	0.0000	C(5)	-0.1037	0.6610	0.5371	0.870	0.901
		C(6)	0.0222	0.8186	0.8504	0.875	0.909
		C(7)	-0.1720	0.1177	0.1386	0.932	0.955
		C(8)	0.1892	0.7833	0.6843	0.963	0.975

Fund: ISG*	E2GARCH(1,2)+tsq	sample ind					
: Z1	M74	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8777	C	0.1518	0.2437	0.2505	0.507	0.511
s.e.	1.6186	ZHG	0.7482	0.0000	0.0000	0.783	0.788
AIC	3.8170	ZHG^2	-0.0063	0.0000	0.1292	0.561	0.561
SBC	3.9604	C(4)	0.7640	0.2387	0.0731	0.680	0.745
J-Bera	0.7324	C(5)	0.2180	0.1337	0.2527	0.666	0.710
		C(6)	0.1279	0.5895	0.4474	0.679	0.741
		C(7)	-0.0682	0.5082	0.5019	0.780	0.838
		C(8)	-0.1451	0.2118	0.1025	0.837	0.862
		C(9)	-0.1600	0.8376	0.7646		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E2GARCH(1,2)+tdm	sample ind					
: Z1	M75	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	C	0.2562	0.1403	0.1839	0.347	0.351
s.e.	1.6325	ZHG	0.8382	0.0000	0.0000	0.589	0.606
AIC	3.8371	ZHG*ZHG_TM	-0.1401	0.0111	0.1831	0.550	0.543
SBC	3.9805	C(4)	0.7507	0.2826	0.1738	0.706	0.779
J-Bera	0.0247	C(5)	0.1952	0.1412	0.3596	0.656	0.737
		C(6)	0.0356	0.8785	0.8782	0.634	0.746
		C(7)	-0.0097	0.9204	0.9290	0.743	0.841
		C(8)	-0.1291	0.2643	0.1933	0.826	0.891
		C(9)	-0.0192	0.9814	0.9810		

Fund: ISG*	E2GARCH(2,2)	sample ind					
: Z1	M76	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8710	C	-0.0695	0.5376	0.4979	0.219	0.223
s.e.	1.6625	ZHG	0.7529	0.0000	0.0000	0.454	0.445
AIC	3.8059	C(3)	1.2797	0.0000	0.0000	0.586	0.655
SBC	3.9493	C(4)	0.2834	0.0257	0.0003	0.720	0.799
J-Bera	0.0381	C(5)	0.0543	0.7043	0.5057	0.827	0.915
		C(6)	-0.0124	0.8504	0.8527	0.899	0.976
		C(7)	-0.1792	0.0035	0.0997	0.916	0.977
		C(8)	0.2209	0.0005	0.0000	0.935	0.983
		C(9)	-0.8732	0.0000	0.0000		

Fund: ISG*	E2GARCH(2,2)+tsq	sample ind					
: Z1	M77	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8766	C	0.0567	0.6378	0.6331	0.434	0.438
s.e.	1.6297	ZHG	0.7481	0.0000	0.0000	0.683	0.684
AIC	3.7909	ZHG^2	-0.0041	0.0027	0.2266	0.840	0.906
SBC	3.9503	C(4)	1.0969	0.0001	0.0000	0.933	0.974
J-Bera	0.7778	C(5)	0.3518	0.0064	0.0008	0.973	0.998
		C(6)	0.0482	0.7636	0.6962	0.989	1.000
		C(7)	-0.0342	0.6564	0.6766	0.992	0.999
		C(8)	-0.1603	0.0972	0.0750	0.973	0.992
		C(9)	0.2207	0.0506	0.0035		
		C(10)	-0.8042	0.0000	0.0000		

Fund: ISG*	E2GARCH(2,2)+tdm	sample ind					
: Z1	M78	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8744	C	0.1318	0.4001	0.4019	0.329	0.334
s.e.	1.6446	ZHG	0.8018	0.0000	0.0000	0.548	0.554
AIC	3.7984	ZHG*ZHG_TM	-0.0971	0.0559	0.2146	0.711	0.802
SBC	3.9578	C(4)	1.1772	0.0000	0.0000	0.832	0.914
J-Bera	0.3490	C(5)	0.3207	0.0100	0.0004	0.912	0.984
		C(6)	0.0476	0.7511	0.6785	0.955	0.997
		C(7)	-0.0313	0.6675	0.6924	0.956	0.993
		C(8)	-0.1786	0.0255	0.0828	0.950	0.989
		C(9)	0.2199	0.0119	0.0005		
		C(10)	-0.8347	0.0000	0.0000		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

P1ARCH(1)
M79

Errors generated – model rejected

P1ARCH(1)+tsq
M80

Errors generated – model rejected

Fund: ISG*	P1ARCH(1)+tdm	sample ind					
: Z1	M81	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	C	0.2452	0.1372	0.1667	0.847	0.848
s.e.	1.6247	ZHG	0.8586	0.0000	0.0000	0.923	0.927
AIC	3.7969	ZHG*ZHG_TM	-0.1458	0.0031	0.1179	0.609	0.587
SBC	3.9084	C(4)	101.9876	0.9146	0.8109	0.741	0.713
J-Bera	0.1545	C(5)	0.0019	0.9367	0.8606	0.739	0.714
		C(6)	-0.0895	0.7089	0.5217	0.677	0.676
		C(7)	11.3359	0.6179	0.2479	0.772	0.783
						0.833	0.823

Fund: ISG*	P1ARCH(1,1)	sample ind					
: Z1	M82	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8709	C	-0.0297	0.7870	0.0000	0.075	0.078
s.e.	1.6546	ZHG	0.7517	0.0000		0.147	0.181
AIC	3.7893	C(3)	1.2995	0.1823	0.0000	0.225	0.233
SBC	3.9008	C(4)	-0.0006	0.0000	0.0025	0.252	0.295
J-Bera	0.1941	C(5)	-0.1729	0.0025	0.0000	0.269	0.262
		C(6)	0.9713	0.0000	0.0000	0.377	0.361
		C(7)	7.1524	0.0000		0.456	0.425
						0.520	0.460

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P1ARCH(1,1)+tsq	sample ind					
: Z1	M83	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8778	C	0.1409	0.2655	0.2292	0.151	0.155
s.e.	1.6138	ZHG	0.7534	0.0000	0.0000	0.347	0.368
AIC	3.7713	ZHG^2	-0.0067	0.0000	0.0235	0.230	0.230
SBC	3.8988	C(4)	1.6105	0.7697	0.5054	0.199	0.269
J-Bera	0.9325	C(5)	-0.0023	0.8321	0.6933	0.274	0.356
		C(6)	-0.0758	0.5977	0.4805	0.383	0.460
		C(7)	0.9143	0.0000	0.0000	0.385	0.423
		C(8)	6.2105	0.2771	0.0069	0.308	0.293

Fund: ISG*	P1ARCH(1,1)+tdm	sample ind					
: Z1	M84	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8749	C	0.2773	0.0498	0.0000	0.068	0.071
s.e.	1.6328	ZHG	0.8363	0.0000	0.0003	0.120	0.153
AIC	3.7746	ZHG*ZHG_TM	-0.1660	0.0003		0.149	0.147
SBC	3.9022	C(4)	0.8295	0.0913	0.0000	0.177	0.211
J-Bera	0.9795	C(5)	-0.0029	0.0000	0.8579	0.232	0.241
		C(6)	-0.0116	0.8579	0.0000	0.334	0.334
		C(7)	0.9604	0.0000	0.0000	0.337	0.302
		C(8)	5.9252	0.0000		0.298	0.211

Fund: ISG*	P1ARCH(2,1)	sample ind					
: Z1	M85	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8720	C	-0.0745	0.4961	0.4942	0.064	0.066
s.e.	1.6515	ZHG	0.7683	0.0000	0.0000	0.175	0.189
AIC	3.7817	C(3)	0.1314	0.3773	0.3353	0.178	0.184
SBC	3.9093	C(4)	-0.0413	0.5903	0.5140	0.211	0.267
J-Bera	0.2598	C(5)	-0.1223	0.2660	0.4414	0.257	0.290
		C(6)	0.5419	0.3597	0.5656	0.364	0.388
		C(7)	0.4726	0.4246	0.6133	0.364	0.379
		C(8)	2.6845	0.2781	0.2886	0.408	0.362

Fund: ISG*	P1ARCH(2,1)+tsq	sample ind					
: Z1	M86	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8776	C	0.1199	0.3310	0.2652	0.710	0.713
s.e.	1.6192	ZHG	0.7515	0.0000	0.0000	0.885	0.884
AIC	3.8038	ZHG^2	-0.0070	0.0000	0.0024	0.513	0.512
SBC	3.9472	C(4)	7.9283	0.5995	0.7267	0.609	0.580
J-Bera	0.7704	C(5)	0.0181	0.7041	0.8194	0.633	0.580
		C(6)	0.3180	0.4317	0.3436	0.717	0.689
		C(7)	0.3206	0.5453	0.3906	0.746	0.729
		C(8)	-0.0762	0.7118	0.6983	0.805	0.780
		C(9)	6.1604	0.1238	0.3686		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P1ARCH(2,1)+tdm	sample ind					
: Z1	M87	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8752	C	0.2721	0.1143	0.0622	0.043	0.045
s.e.	1.6348	ZHG	0.8428	0.0000	0.0000	0.120	0.137
AIC	3.7867	ZHG*ZHG_TM	-0.1665	0.0049	0.0107	0.109	0.110
SBC	3.9302	C(4)	0.5130	0.5709	0.2481	0.128	0.174
J-Bera	0.9217	C(5)	-0.0102	0.7475	0.6884	0.194	0.246
		C(6)	-0.0472	0.6018	0.6582	0.281	0.323
		C(7)	0.6191	0.3961	0.5921	0.257	0.287
		C(8)	0.3464	0.6255	0.7553	0.227	0.190
		C(9)	4.6131	0.2237	0.0970		

Fund: ISG*	P1ARCH(1,2)	sample ind					
: Z1	M88	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0544	0.6204	0.6084	0.492	0.496
s.e.	1.6485	ZHG	0.7829	0.0000	0.0000	0.710	0.722
AIC	3.8123	C(3)	1.1472	0.4730	0.4257	0.760	0.780
SBC	3.9398	C(4)	0.0557	0.3878	0.8803	0.844	0.843
J-Bera	0.0023	C(5)	0.0114	0.7471	0.9151	0.746	0.770
		C(6)	-0.0503	0.4009	0.8645	0.840	0.851
		C(7)	0.8460	0.0000	0.4136	0.900	0.908
		C(8)	4.8873	0.1032	0.7242	0.943	0.942

Fund: ISG*	P1ARCH(1,2)+tsq	sample ind					
: Z1	M89	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8778	C	0.1144	0.3771	0.3604	0.934	0.935
s.e.	1.6177	ZHG	0.7608	0.0000	0.0000	0.787	0.791
AIC	3.8023	ZHG^2	-0.0066	0.0000	0.0861	0.524	0.499
SBC	3.9457	C(4)	2.0453	0.6286	0.6702	0.669	0.658
J-Bera	0.8639	C(5)	0.0700	0.6014	0.5249	0.638	0.662
		C(6)	0.1568	0.6237	0.4460	0.718	0.758
		C(7)	-0.0442	0.6901	0.6903	0.779	0.796
		C(8)	0.4967	0.2323	0.4329	0.786	0.777
		C(9)	3.3526	0.3897	0.2901		

Fund: ISG*	P1ARCH(1,2)+tdm	sample ind					
: Z1	M90	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	C	0.2478	0.2082	0.1486	0.845	0.847
s.e.	1.6323	ZHG	0.8561	0.0000	0.0000	0.936	0.938
AIC	3.8084	ZHG*ZHG_TM	-0.1556	0.0119	0.0818	0.589	0.597
SBC	3.9519	C(4)	1.3612	0.8827	0.7928	0.608	0.609
J-Bera	0.5968	C(5)	0.0374	0.8673	0.7616	0.670	0.695
		C(6)	-0.0085	0.9333	0.8245	0.783	0.814
		C(7)	-0.0318	0.8696	0.7591	0.769	0.769
		C(8)	0.8737	0.0001	0.0033	0.796	0.801
		C(9)	5.1963	0.6924	0.4242		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P1ARCH(2,2)	sample ind					
: Z1	M91	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8720	C	-0.0726	0.5101	0.5064	0.852	0.853
s.e.	1.6557	ZHG	0.8036	0.0000	0.0000	0.820	0.826
AIC	3.8468	C(3)	2.4536	0.4714	0.1828	0.939	0.911
SBC	3.9903	C(4)	0.0731	0.5180	0.5394	0.982	0.973
J-Bera	0.0000	C(5)	-0.0387	0.8615	0.8224	0.940	0.952
		C(6)	-0.0428	0.6570	0.4959	0.840	0.858
		C(7)	0.5841	0.3904	0.0506	0.902	0.913
		C(8)	-0.1895	0.5625	0.6766	0.945	0.940
		C(9)	3.1855	0.2233	0.1286		

Fund: ISG*	P1ARCH(2,2)+tsq	sample ind					
: Z1	M92	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8778	C	0.1109	0.3894	0.3701	0.986	0.987
s.e.	1.6218	ZHG	0.7599	0.0000	0.0000	0.842	0.846
AIC	3.8103	ZHG^2	-0.0065	0.0000	0.0855	0.537	0.518
SBC	3.9697	C(4)	2.6443	0.6753	0.6930	0.679	0.669
J-Bera	0.8686	C(5)	0.0577	0.6760	0.6060	0.666	0.681
		C(6)	0.1500	0.6262	0.4811	0.745	0.776
		C(7)	-0.0305	0.7538	0.7502	0.798	0.812
		C(8)	0.4655	0.4788	0.4764	0.811	0.804
		C(9)	-0.0051	0.9892	0.9758		
		C(10)	3.8720	0.4070	0.3064		

P1ARCH(2,2)+tdm
M93

Errors generated – model rejected

Fund: ISG*	P2ARCH(1,2)	sample ind					
: Z1	M94	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8723	C	-0.0278	0.8083	0.7989	0.981	0.981
s.e.	1.6540	ZHG	0.7982	0.0000	0.0000	0.925	0.927
AIC	3.8401	C(3)	2.8589	0.7144	0.7017	0.925	0.914
SBC	3.9835	C(4)	0.0539	0.7555	0.7316	0.972	0.967
J-Bera	0.0001	C(5)	-0.2170	0.5466	0.2270	0.902	0.906
		C(6)	-0.0360	0.7819	0.7581	0.888	0.891
		C(7)	-0.2181	0.4937	0.1625	0.937	0.940
		C(8)	0.5811	0.2630	0.0982	0.967	0.964
		C(9)	4.3981	0.4536	0.4043		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P2ARCH(1,2)+tsq	sample ind					
: Z1	M95	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	C	0.1395	0.2594	0.2592	0.632	0.635
s.e.	1.6210	ZHG	0.7646	0.0000	0.0000	0.495	0.509
AIC	3.8124	ZHG^2	-0.0064	0.0000	0.0654	0.459	0.400
SBC	3.9718	C(4)	2.5356	0.4685	0.3456	0.615	0.589
J-Bera	0.9030	C(5)	0.0599	0.5063	0.4210	0.610	0.688
		C(6)	0.1723	0.6713	0.6245	0.677	0.759
		C(7)	-0.0281	0.7821	0.7019	0.765	0.816
		C(8)	-0.2322	0.8424	0.7936	0.752	0.769
		C(9)	0.3283	0.4243	0.2147		
		C(10)	3.0957	0.2946	0.1297		

Fund: ISG*	P2ARCH(1,2)+tdm	sample ind					
: Z1	M96	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8742	C	0.2885	0.0693	0.0504	0.220	0.224
s.e.	1.6457	ZHG	0.8379	0.0000	0.0000	0.435	0.454
AIC	3.7548	ZHG*ZHG_TM	-0.1842	0.0007	0.0032	0.302	0.342
SBC	3.9142	C(4)	0.2677	0.5655	0.2771	0.400	0.397
J-Bera	0.8885	C(5)	0.0223	0.6896	0.5419	0.385	0.410
		C(6)	-0.0371	0.9398	0.8796	0.510	0.561
		C(7)	-0.0348	0.6486	0.4655	0.391	0.381
		C(8)	-0.0247	0.9366	0.8762	0.350	0.367
		C(9)	1.0048	0.0000	0.0000		
		C(10)	4.3944	0.1996	0.0296		

Fund: ISG*	P2ARCH(2,2)	sample ind					
: Z1	M97	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	C	-0.0374	0.7491	0.7266	0.919	0.920
s.e.	1.6569	ZHG	0.7791	0.0000	0.0000	0.766	0.763
AIC	3.8242	C(3)	3.4896	0.0761	0.0097	0.861	0.844
SBC	3.9836	C(4)	0.1603	0.1420	0.0974	0.941	0.938
J-Bera	0.0005	C(5)	-0.0642	0.7844	0.7301	0.977	0.990
		C(6)	-0.0246	0.9521	0.9557	0.983	0.993
		C(7)	-0.8803	0.9540	0.9555	0.846	0.885
		C(8)	0.0380	0.9087	0.9348	0.905	0.928
		C(9)	-0.5271	0.0390	0.0337		
		C(10)	1.9233	0.0272	0.0007		

Fund: ISG*	P2ARCH(2,2)+tsq	sample ind					
: Z1	M98	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	C	0.1208	0.3626	0.3358	0.793	0.795
s.e.	1.6255	ZHG	0.7667	0.0000	0.0000	0.579	0.578
AIC	3.8112	ZHG^2	-0.0054	0.0001	0.1398	0.748	0.705
SBC	3.9865	C(4)	3.3126	0.2000	0.1818	0.861	0.841
J-Bera	0.9509	C(5)	0.1280	0.2817	0.1020	0.910	0.953
		C(6)	0.1814	0.5382	0.5451	0.928	0.949
		C(7)	-0.0179	0.9639	0.9556	0.963	0.975
		C(8)	-0.6813	0.9633	0.9553	0.927	0.937
		C(9)	0.0846	0.8545	0.8652		
		C(10)	-0.2919	0.2794	0.3014		
		C(11)	2.3744	0.1468	0.0397		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P2ARCH(2,2)+tdm	sample ind					
: Z1	M99	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8755	C	0.2179	0.2172	0.2175	0.913	0.914
s.e.	1.6412	ZHG	0.8375	0.0000	0.0000	0.579	0.580
AIC	3.8240	ZHG*ZHG_TM	-0.1136	0.0366	0.2065	0.778	0.743
SBC	3.9993	C(4)	3.7630	0.2986	0.0933	0.890	0.886
J-Bera	0.2337	C(5)	0.1408	0.2689	0.0771	0.938	0.968
		C(6)	-0.0038	0.9876	0.9838	0.948	0.971
		C(7)	-0.0143	0.9903	0.9852	0.942	0.961
		C(8)	-0.8925	0.9892	0.9835	0.953	0.965
		C(9)	-0.0222	0.9646	0.9560		
		C(10)	-0.3573	0.1968	0.2342		
		C(11)	2.3100	0.1810	0.0279		

Fund: ISG*	ARCH-M(1)	sample ind					
: Z1	M100	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	@SQRT(GARCH)	0.0053	0.9959	0.9957	0.765	0.767
s.e.	1.6367	C	-0.0618	0.9698	0.9688	0.844	0.849
AIC	3.8264	ZHG	0.7924	0.0000	0.0000	0.883	0.863
SBC	3.9061	C	2.3184	0.0000	0.0000	0.941	0.938
J-Bera	0.0000	RESID(-1)^2	0.1061	0.1703	0.3504	0.936	0.946
						0.905	0.918
						0.950	0.959
						0.975	0.978

Fund: ISG*	ARCH-M(1)+tsq	sample ind					
: Z1	M101	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8781	@SQRT(GARCH)	0.1116	0.9140	0.9121	0.652	0.655
s.e.	1.6043	C	-0.0388	0.9806	0.9803	0.784	0.790
AIC	3.7902	ZHG	0.7624	0.0000	0.0000	0.445	0.420
SBC	3.8858	ZHG^2	-0.0058	0.0000	0.1654	0.562	0.583
J-Bera	0.7797	C	2.1933	0.0000	0.0000	0.544	0.569
		RESID(-1)^2	0.1132	0.1615	0.2636	0.578	0.637
						0.684	0.733
						0.671	0.674

Fund: ISG*	ARCH-M(1)+tdm	sample ind					
: Z1	M102	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	@SQRT(GARCH)	-0.0276	0.9777	0.9795	0.596	0.599
s.e.	1.6202	C	0.2926	0.8476	0.8637	0.684	0.696
AIC	3.8067	ZHG	0.8532	0.0000	0.0000	0.530	0.501
SBC	3.9024	ZHG*ZHG_TM	-0.1486	0.0016	0.1556	0.692	0.706
J-Bera	0.0855	C	2.2432	0.0000	0.0000	0.678	0.713
		RESID(-1)^2	0.1078	0.1589	0.3019	0.660	0.731
						0.764	0.819
						0.820	0.853

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	GARCH-M(1,1)	sample ind					
: Z1	M103	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8709	@SQRT(GARCH)	0.5159	0.0000	0.3845	0.055	0.057
s.e.	1.6505	C	-0.8113	0.0000	0.3717	0.029	0.048
AIC	3.7709	ZHG	0.7600	0.0000	0.0000	0.059	0.086
SBC	3.8665	C	0.0189	0.1960	0.5791	0.094	0.162
J-Bera	0.0000	RESID(-1)^2	-0.0354	0.0000	0.0049	0.099	0.230
		GARCH(-1)	1.0209	0.0000	0.0000	0.054	0.192
						0.040	0.215
						0.064	0.247

Fund: ISG*	GARCH-M(1,1)+tsq	sample ind					
: Z1	M104	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8782	@SQRT(GARCH)	0.3693	0.4693	0.4458	0.000	0.000
s.e.	1.6072	C	-0.4660	0.5167	0.5006	0.000	0.000
AIC	3.7194	ZHG	0.7563	0.0000	0.0000	0.000	0.000
SBC	3.8310	ZHG^2	-0.0067	0.0000	0.0134	0.000	0.000
J-Bera	0.0000	C	0.0982	0.0000	0.0051	0.000	0.000
		RESID(-1)^2	-0.0617	0.0000	0.0019	0.000	0.000
		GARCH(-1)	1.0168	0.0000	0.0000	0.000	0.000
						0.000	0.000

Fund: ISG*	GARCH-M(1,1)+tdm	sample ind					
: Z1	M105	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	@SQRT(GARCH)	0.4450	0.3460	0.3942	0.000	0.000
s.e.	1.6236	C	-0.3792	0.5293	0.6123	0.000	0.000
AIC	3.7200	ZHG	0.8488	0.0000	0.0000	0.000	0.000
SBC	3.8316	ZHG*ZHG_TM	-0.1825	0.0001	0.0078	0.000	0.000
J-Bera	0.0000	C	0.0751	0.0000	0.0035	0.000	0.000
		RESID(-1)^2	-0.0545	0.0000	0.0069	0.000	0.000
		GARCH(-1)	1.0197	0.0000	0.0000	0.000	0.000
						0.000	0.000

Fund: ISG*	GARCH-M(2,1)	sample ind					
: Z1	M106	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8721	@SQRT(GARCH)	-0.4960	0.2607	0.4973	0.110	0.113
s.e.	1.6472	C	0.7102	0.2827	0.5098	0.237	0.267
AIC	3.7604	ZHG	0.7652	0.0000	0.0000	0.000	0.000
SBC	3.8719	C	0.0785	0.0875	0.4248	0.000	0.001
J-Bera	0.0000	RESID(-1)^2	-0.0856	0.0000	0.0657	0.001	0.003
		GARCH(-1)	0.4350	0.1239	0.4461	0.001	0.002
		GARCH(-2)	0.6165	0.0266	0.2843	0.003	0.004
						0.005	0.007

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	GARCH-M(2,1)+tsq	sample ind					
: Z1	M107	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8787	@SQRT(GARCH)	0.5689	0.2400	0.2281	0.001	0.001
s.e.	1.6083	C	-0.7901	0.2714	0.2571	0.005	0.005
AIC	3.7516	ZHG	0.7630	0.0000	0.0000	0.012	0.009
SBC	3.8791	ZHG^2	-0.0068	0.0000	0.0097	0.027	0.024
J-Bera	0.0209	C	0.1602	0.0150	0.0046	0.020	0.024
		RESID(-1)^2	-0.0925	0.0000	0.0072	0.018	0.038
		GARCH(-1)	0.1636	0.2567	0.1310	0.010	0.033
		GARCH(-2)	0.8520	0.0000	0.0000	0.015	0.051

Fund: ISG*	GARCH-M(2,1)+tdm	sample ind					
: Z1	M108	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8761	@SQRT(GARCH)	0.6364	0.1772	0.2377	0.004	0.004
s.e.	1.6254	C	-0.6710	0.2732	0.3956	0.005	0.012
AIC	3.7409	ZHG	0.8558	0.0000	0.0000	0.015	0.017
SBC	3.8684	ZHG*ZHG_TM	-0.1859	0.0002	0.0088	0.022	0.029
J-Bera	0.0000	C	0.0844	0.0000	0.4123	0.022	0.049
		RESID(-1)^2	-0.0595	0.0000	0.4483	0.011	0.050
		GARCH(-1)	0.7623	0.0000	0.6535	0.004	0.039
		GARCH(-2)	0.2559	0.0000	0.8820	0.007	0.046

Fund: ISG*	GARCH-M(1,2)	sample ind					
: Z1	M109	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8724	@SQRT(GARCH)	-0.6337	0.1290	0.3068	0.412	0.416
s.e.	1.6453	C	0.9287	0.1218	0.3003	0.590	0.612
AIC	3.7405	ZHG	0.7683	0.0000	0.0000	0.686	0.683
SBC	3.8520	C	0.0660	0.0000	0.1646	0.802	0.820
J-Bera	0.4603	RESID(-1)^2	0.0321	0.0022	0.5501	0.432	0.437
		RESID(-2)^2	-0.0760	0.0000	0.1632	0.551	0.566
		GARCH(-1)	1.0161	0.0000	0.0000	0.658	0.655
						0.665	0.633

Fund: ISG*	GARCH-M(1,2)+tsq	sample ind					
: Z1	M110	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8786	@SQRT(GARCH)	0.8113	0.0040	0.0006	0.513	0.517
s.e.	1.6086	C	-1.0201	0.0095	0.0025	0.758	0.752
AIC	3.7453	ZHG	0.7430	0.0000	0.0000	0.716	0.736
SBC	3.8728	ZHG^2	-0.0081	0.0000	0.0121	0.757	0.754
J-Bera	0.7086	C	0.2566	0.0013	0.0000	0.790	0.827
		RESID(-1)^2	0.0484	0.0039	0.5275	0.875	0.904
		RESID(-2)^2	-0.1124	0.0000	0.1283	0.832	0.845
		GARCH(-1)	0.9532	0.0000	0.0000	0.651	0.676

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	GARCH-M(1,2)+tdm	sample ind					
: Z1	M111	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	@SQRT(GARCH)	0.3317	0.4665	0.5228	0.000	0.000
s.e.	1.6275	C	-0.2292	0.7090	0.7551	0.000	0.000
AIC	3.7156	ZHG	0.8379	0.0000	0.0000	0.000	0.000
SBC	3.8431	ZHG*ZHG_TM	-0.1632	0.0011	0.0180	0.000	0.000
J-Bera	0.0000	C	0.0733	0.0000	0.0141	0.000	0.000
		RESID(-1)^2	-0.0026	0.9372	0.9694	0.000	0.000
		RESID(-2)^2	-0.0560	0.1204	0.3735	0.000	0.000
		GARCH(-1)	1.0263	0.0000	0.0000	0.000	0.000

Fund: ISG*	GARCH-M(2,2)	sample ind					
: Z1	M112	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8719	@SQRT(GARCH)	0.2638	0.4726	0.6530	0.000	0.000
s.e.	1.6526	C	-0.4620	0.3881	0.5690	0.000	0.001
AIC	3.7718	ZHG	0.7685	0.0000	0.0000	0.001	0.003
SBC	3.8993	C	0.1024	0.0000	0.0608	0.002	0.008
J-Bera	0.0000	RESID(-1)^2	-0.0483	0.0000	0.0416	0.001	0.006
		RESID(-2)^2	-0.0340	0.0003	0.2214	0.001	0.011
		GARCH(-1)	0.0492	0.1567	0.6079	0.001	0.019
		GARCH(-2)	0.9856	0.0000	0.0000	0.002	0.032

GARCH-M(2,2)+tsq
M113

Errors generated – model rejected

Fund: ISG*	GARCH-M(2,2)+tdm	sample ind					
: Z1	M114	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	@SQRT(GARCH)	0.1696	0.0000	0.7388	0.000	0.000
s.e.	1.6324	C	-0.0079	0.9617	0.9912	0.000	0.000
AIC	3.7311	ZHG	0.8330	0.0000	0.0000	0.000	0.000
SBC	3.8746	ZHG*ZHG_TM	-0.1477	0.0001	0.0316	0.000	0.000
J-Bera	0.0000	C	0.0821	0.0000	0.2937	0.000	0.000
		RESID(-1)^2	-0.0013	0.9636	0.9848	0.000	0.000
		RESID(-2)^2	-0.0619	0.0352	0.3874	0.000	0.000
		GARCH(-1)	0.9039	0.0000	0.3932	0.000	0.000
		GARCH(-2)	0.1231	0.0000	0.9100		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH-M(1)	sample ind					
: Z1	M115	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8772	@SQRT(GARCH)	29.1654	0.8555	0.7414	0.039	0.040
s.e.	1.6097	C	-46.5109	0.8550	0.7437	0.115	0.116
AIC	3.8194	ZHG	0.7825	0.0000	0.0000	0.199	0.249
SBC	3.9150	C	2.5406	0.0000	0.0000	0.324	0.507
J-Bera	0.0000	RESID(-1)^2	-0.0085	0.8573	0.7314	0.453	0.511
		RESID(-1)^2*(RESID(-1)<0)	0.0149	0.8597	0.7310	0.415	0.516
						0.360	0.314
						0.205	0.241

Fund: ISG*	T1ARCH-M(1)+tsq	sample ind					
: Z1	M116	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8781	@SQRT(GARCH)	0.1155	0.9197	0.9075	0.655	0.658
s.e.	1.6082	C	-0.0449	0.9796	0.9769	0.784	0.790
AIC	3.7997	ZHG	0.7623	0.0000	0.0000	0.446	0.421
SBC	3.9113	ZHG^2	-0.0058	0.0000	0.1633	0.563	0.584
J-Bera	0.7802	C	2.1935	0.0000	0.0000	0.546	0.571
		RESID(-1)^2	0.1123	0.2487	0.3703	0.580	0.639
		RESID(-1)^2*(RESID(-1)<0)	0.0016	0.9915	0.9921	0.685	0.734
						0.672	0.675

Fund: ISG*	T1ARCH-M(1)+tdm	sample ind					
: Z1	M117	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8817	@SQRT(GARCH)	-3.0587	0.1632	0.0000	0.819	0.821
s.e.	1.5842	C	4.9524	0.1396	0.0000	0.114	0.121
AIC	3.7715	ZHG	0.8406	0.0000	0.0000	0.084	0.099
SBC	3.8831	ZHG*ZHG_TM	-0.1451	0.0005	0.0576	0.134	0.179
J-Bera	0.0917	C	2.3885	0.0000	0.0000	0.187	0.216
		RESID(-1)^2	0.0691	0.2467	0.1801	0.249	0.314
		RESID(-1)^2*(RESID(-1)<0)	-0.1364	0.1685	0.0060	0.344	0.382
						0.363	0.407

T1ARCH-M(1,1)
M118

Errors generated – model rejected

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH-M(1,1)+tsq	sample ind					
: Z1	M119	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8817	@SQRT(GARCH)	1.2917	0.0422	0.0267	0.512	0.516
s.e.	1.5877	C	-1.7164	0.0513	0.0346	0.720	0.717
AIC	3.6982	ZHG	0.7524	0.0000	0.0000	0.844	0.856
SBC	3.8257	ZHG^2	-0.0089	0.0000	0.0002	0.931	0.959
J-Bera	0.6103	C	0.1132	0.0000	0.0000	0.966	0.965
		RESID(-1)^2	-0.0756	0.0000	0.0012	0.983	0.967
		RESID(-1)^2*(RESID(-1)<0)	0.0411	0.0001	0.0853	0.756	0.738
		GARCH(-1)	1.0044	0.0000	0.0000	0.830	0.817

Fund: ISG*	T1ARCH-M(1,1)+tdm	sample ind					
: Z1	M120	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8756	@SQRT(GARCH)	0.3101	0.5161	0.5378	0.000	0.000
s.e.	1.6287	C	-0.2122	0.7371	0.7658	0.000	0.000
AIC	3.7256	ZHG	0.8418	0.0000	0.0000	0.000	0.000
SBC	3.8531	ZHG*ZHG_TM	-0.1673	0.0016	0.0127	0.000	0.000
J-Bera	0.0000	C	0.0718	0.0000	0.0402	0.000	0.000
		RESID(-1)^2	-0.0567	0.0000	0.0584	0.000	0.000
		RESID(-1)^2*(RESID(-1)<0)	-0.0018	0.8658	0.9494	0.000	0.000
		GARCH(-1)	1.0248	0.0000	0.0000	0.000	0.000

Fund: ISG*	T1ARCH-M(2,1)	sample ind					
: Z1	M121	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8743	@SQRT(GARCH)	0.4792	0.1190	0.0000	0.981	0.981
s.e.	1.6371	C	-0.7545	0.0992	0.0000	0.927	0.921
AIC	3.7966	ZHG	0.7931	0.0000	0.0000	0.985	0.977
SBC	3.9242	C	2.5484	0.0000	0.0316	0.996	0.993
J-Bera	0.0000	RESID(-1)^2	0.1696	0.0369	0.3662	0.999	0.997
		RESID(-1)^2*(RESID(-1)<0)	0.0179	0.8855	0.8327	0.974	0.962
		GARCH(-1)	0.2891	0.0007	0.0001	0.784	0.753
		GARCH(-2)	-0.4513	0.0001	0.1511	0.859	0.818

Fund: ISG*	T1ARCH-M(2,1)+tsq	sample ind					
: Z1	M122	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8809	@SQRT(GARCH)	1.5149	0.0094	0.0043	0.473	0.477
s.e.	1.5974	C	-2.1231	0.0118	0.0050	0.692	0.696
AIC	3.7217	ZHG	0.7435	0.0000	0.0000	0.837	0.858
SBC	3.8651	ZHG^2	-0.0081	0.0000	0.0004	0.927	0.964
J-Bera	0.7841	C	0.1842	0.0000	0.0077	0.969	0.968
		RESID(-1)^2	-0.1245	0.0000	0.0042	0.988	0.977
		RESID(-1)^2*(RESID(-1)<0)	0.0713	0.0000	0.1573	0.860	0.829
		GARCH(-1)	0.1835	0.0000	0.2198	0.905	0.888
		GARCH(-2)	0.8208	0.0000	0.0000		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH-M(2,1)+tdm	sample ind					
: Z1	M123	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8757	@SQRT(GARCH)	0.8809	0.0522	0.0396	0.682	0.684
s.e.	1.6318	C	-0.9387	0.1408	0.1375	0.749	0.768
AIC	3.7799	ZHG	0.8659	0.0000	0.0000	0.866	0.793
SBC	3.9234	ZHG*ZHG_TM	-0.2246	0.0000	0.0034	0.946	0.898
J-Bera	0.6218	C	0.1513	0.0000	0.0178	0.961	0.940
		RESID(-1)^2	-0.0848	0.0000	0.0739	0.975	0.959
		RESID(-1)^2*(RESID(-1)<0)	0.0672	0.0199	0.0638	0.948	0.942
		GARCH(-1)	0.9724	0.0000	0.0662	0.974	0.968
		GARCH(-2)	0.0161	0.0000	0.9761		

T1ARCH-M(1,2)
M124

Errors generated – model rejected

Fund: ISG*	T1ARCH-M(1,2)+tsq	sample ind					
: Z1	M125	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8806	@SQRT(GARCH)	1.1260	0.0327	0.0275	0.582	0.585
s.e.	1.5993	C	-1.4700	0.0447	0.0370	0.707	0.703
AIC	3.7134	ZHG	0.7460	0.0000	0.0000	0.834	0.816
SBC	3.8568	ZHG^2	-0.0088	0.0000	0.0006	0.915	0.926
J-Bera	0.6696	C	0.1219	0.0000	0.0002	0.952	0.954
		RESID(-1)^2	-0.0097	0.0000	0.8527	0.979	0.965
		RESID(-1)^2*(RESID(-1)<0)	0.0294	0.0000	0.3048	0.721	0.704
		RESID(-2)^2	-0.0698	0.0000	0.1228	0.799	0.789
		GARCH(-1)	1.0117	0.0000	0.0000		

T1ARCH-M(1,2)+tdm
M126

Errors generated – model rejected

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T1ARCH-M(2,2)	sample ind					
: Z1	M127	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8739	@SQRT(GARCH)	-1.0308	0.0154	0.0615	0.102	0.105
s.e.	1.6436	C	1.5101	0.0146	0.0618	0.062	0.085
AIC	3.7436	ZHG	0.7715	0.0000	0.0000	0.068	0.060
SBC	3.8870	C	0.0854	0.0000	0.1824	0.128	0.130
J-Bera	0.0000	RESID(-1)^2	0.0386	0.5280	0.4466	0.039	0.026
		RESID(-1)^2*(RESID(-1)<0)	-0.0240	0.0010	0.6742	0.050	0.038
		RESID(-2)^2	-0.0919	0.1069	0.0656	0.079	0.058
		GARCH(-1)	0.6466	0.0000	0.0688	0.111	0.094
		GARCH(-2)	0.3818	0.0000	0.2946		

Fund: ISG*	T1ARCH-M(2,2)+tsq	sample ind					
: Z1	M128	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8794	@SQRT(GARCH)	0.8688	0.1050	0.1090	0.771	0.773
s.e.	1.6112	C	-1.0779	0.1547	0.1426	0.807	0.821
AIC	3.7388	ZHG	0.7460	0.0000	0.0000	0.854	0.765
SBC	3.8982	ZHG^2	-0.0085	0.0000	0.0030	0.935	0.869
J-Bera	0.6441	C	0.1019	0.0000	0.2665	0.934	0.907
		RESID(-1)^2	-0.0250	0.1431	0.6694	0.971	0.942
		RESID(-1)^2*(RESID(-1)<0)	0.0161	0.2150	0.5440	0.759	0.723
		RESID(-2)^2	-0.0328	0.0070	0.6727	0.826	0.787
		GARCH(-1)	1.1754	0.0000	0.1615		
		GARCH(-2)	-0.1708	0.0000	0.8408		

Fund: ISG*	T1ARCH-M(2,2)+tdm	sample ind					
: Z1	M129	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8772	@SQRT(GARCH)	1.5113	0.0077	0.0138	0.557	0.561
s.e.	1.6261	C	-1.8627	0.0184	0.0347	0.802	0.802
AIC	3.7480	ZHG	0.8725	0.0000	0.0000	0.928	0.941
SBC	3.9073	ZHG*ZHG_TM	-0.2381	0.0000	0.0008	0.967	0.984
J-Bera	0.8942	C	0.1766	0.0000	0.0131	0.988	0.988
		RESID(-1)^2	-0.0893	0.0007	0.0250	0.996	0.994
		RESID(-1)^2*(RESID(-1)<0)	0.0550	0.0224	0.2063	0.967	0.953
		RESID(-2)^2	-0.0180	0.0915	0.7272	0.984	0.976
		GARCH(-1)	0.2189	0.0000	0.5683		
		GARCH(-2)	0.7806	0.0000	0.0379		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH-M(1)	sample ind					
: Z1	M130	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8790	@SQRT(GARCH)	29.1735	0.8555	0.7322	0.036	0.038
s.e.	1.6023	C	-46.2715	0.8550	0.7349	0.109	0.110
AIC	3.8147	ZHG	0.7780	0.0000	0.0000	0.191	0.239
SBC	3.9263	C	2.5062	0.0000	0.0000	0.313	0.495
J-Bera	0.0000	RESID(-1)^2	-0.0074	0.8587	0.7225	0.441	0.496
		RESID(-1)^2*(RESID(-1)<0)	0.0128	0.8596	0.7210	0.402	0.500
		RESID(-2)^2*(RESID(-2)<0)	0.0045	0.8609	0.7318	0.345	0.295
						0.196	0.229

Fund: ISG*	T2ARCH-M(1)+tsq	sample ind					
: Z1	M131	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8825	@SQRT(GARCH)	5.3253	0.5859	0.4936	0.000	0.000
s.e.	1.5823	C	-8.1587	0.5893	0.4998	0.000	0.000
AIC	3.7891	ZHG	0.7544	0.0000	0.0000	0.000	0.000
SBC	3.9167	ZHG^2	-0.0049	0.0000	0.1617	0.000	0.000
J-Bera	0.0000	C	2.3623	0.0000	0.0000	0.000	0.189
		RESID(-1)^2	-0.0301	0.6109	0.4705	0.000	0.073
		RESID(-1)^2*(RESID(-1)<0)	0.0697	0.5942	0.4582	0.000	0.000
		RESID(-2)^2*(RESID(-2)<0)	0.0282	0.6164	0.5629	0.000	0.000

Fund: ISG*	T2ARCH-M(1)+tdm	sample ind					
: Z1	M132	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8821	@SQRT(GARCH)	10.7839	0.7558	0.6386	0.496	0.499
s.e.	1.5850	C	-16.5854	0.7583	0.6446	0.782	0.787
AIC	3.7962	ZHG	0.8352	0.0000	0.0000	0.872	0.888
SBC	3.9237	ZHG*ZHG_TM	-0.1349	0.0039	0.1278	0.863	0.877
J-Bera	0.0000	C	2.4112	0.0000	0.0000	0.836	0.846
		RESID(-1)^2	-0.0184	0.7597	0.6191	0.898	0.901
		RESID(-1)^2*(RESID(-1)<0)	0.0372	0.7622	0.6199	0.923	0.918
		RESID(-2)^2*(RESID(-2)<0)	0.0140	0.7695	0.6483	0.957	0.952

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

T2ARCH-M(1,1)
M133 |
|
Errors generated – model rejected

Fund: ISG*	T2ARCH-M(1,1)+tsq	sample ind					
: Z1	M134	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8825	@SQRT(GARCH)	1.6772	0.0000	0.0006	0.907	0.908
s.e.	1.5869	C	-2.2038	0.0001	0.0008	0.888	0.889
AIC	3.7049	ZHG	0.7332	0.0000	0.0000	0.970	0.960
SBC	3.8484	ZHG^2	-0.0113	0.0000	0.0000	0.953	0.945
J-Bera	0.4536	C	0.1720	0.0000	0.0000	0.981	0.962
		RESID(-1)^2	-0.0852	0.0000	0.0001	0.980	0.964
		RESID(-1)^2*(RESID(-1)<0)	0.1848	0.0380	0.0109	0.933	0.884
		RESID(-2)^2*(RESID(-2)<0)	-0.1364	0.1383	0.0473	0.907	0.857
		GARCH(-1)	0.9841	0.0000	0.0000		

Fund: ISG*	T2ARCH-M(1,1)+tdm	sample ind					
: Z1	M135	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8762	@SQRT(GARCH)	0.4080	0.3725	0.4088	0.004	0.004
s.e.	1.6289	C	-0.3492	0.5655	0.6228	0.000	0.000
AIC	3.7286	ZHG	0.8410	0.0000	0.0000	0.000	0.000
SBC	3.8720	ZHG*ZHG_TM	-0.1674	0.0014	0.0152	0.000	0.001
J-Bera	0.0000	C	0.0775	0.0000	0.0075	0.000	0.001
		RESID(-1)^2	-0.0544	0.0000	0.0505	0.000	0.001
		RESID(-1)^2*(RESID(-1)<0)	0.0698	0.4799	0.3741	0.000	0.001
		RESID(-2)^2*(RESID(-2)<0)	-0.0768	0.4663	0.3170	0.000	0.001
		GARCH(-1)	1.0215	0.0000	0.0000		

T2ARCH-M(2,1)
M136 |

Errors generated – model rejected

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH-M(2,1)+tsq	sample ind					
: Z1	M137	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8827	@SQRT(GARCH)	1.4199	0.0185	0.0093	0.510	0.514
s.e.	1.5889	C	-1.8629	0.0238	0.0137	0.715	0.715
AIC	3.7118	ZHG	0.7475	0.0000	0.0000	0.833	0.848
SBC	3.8712	ZHG^2	-0.0093	0.0000	0.0001	0.929	0.958
J-Bera	0.6054	C	0.1533	0.0001	0.0008	0.968	0.964
		RESID(-1)^2	-0.1007	0.0000	0.0251	0.981	0.962
		RESID(-1)^2*(RESID(-1)<0)	0.0810	0.0603	0.3239	0.804	0.782
		RESID(-2)^2*(RESID(-2)<0)	-0.0189	0.6778	0.7980	0.873	0.855
		GARCH(-1)	0.6876	0.0799	0.1422		
		GARCH(-2)	0.3122	0.4159	0.5129		

Fund: ISG*	T2ARCH-M(2,1)+tdm	sample ind					
: Z1	M138	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8780	@SQRT(GARCH)	1.0667	0.0003	0.0030	0.316	0.320
s.e.	1.6209	C	-1.1599	0.0078	0.0250	0.586	0.560
AIC	3.7573	ZHG	0.8548	0.0000	0.0000	0.637	0.641
SBC	3.9167	ZHG*ZHG_TM	-0.2360	0.0000	0.0020	0.724	0.708
J-Bera	0.9518	C	0.1849	0.0000	0.0000	0.839	0.823
		RESID(-1)^2	-0.0472	0.0068	0.0030	0.911	0.903
		RESID(-1)^2*(RESID(-1)<0)	0.2251	0.0000	0.0034	0.829	0.810
		RESID(-2)^2*(RESID(-2)<0)	-0.2180	0.0000	0.0042	0.831	0.831
		GARCH(-1)	1.2423	0.0000	0.0000		
		GARCH(-2)	-0.2793	0.0000	0.0252		

T2ARCH-M(1,2)
M139

Errors generated – model rejected

Fund: ISG*	T2ARCH-M(1,2)+tsq	sample ind					
: Z1	M140	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8772	@SQRT(GARCH)	0.9853	0.0000	0.0209	0.718	0.721
s.e.	1.6263	C	-1.2269	0.0000	0.0307	0.669	0.669
AIC	3.7500	ZHG	0.7294	0.0000	0.0000	0.830	0.793
SBC	3.9094	ZHG^2	-0.0097	0.0000	0.0004	0.923	0.907
J-Bera	0.8174	C	0.1870	0.0000	0.0000	0.956	0.962
		RESID(-1)^2	-0.0330	0.5077	0.5687	0.980	0.982
		RESID(-1)^2*(RESID(-1)<0)	0.1122	0.0000	0.2616	0.951	0.961
		RESID(-2)^2	-0.0546	0.2712	0.3175	0.927	0.927
		RESID(-2)^2*(RESID(-2)<0)	-0.0879	0.0000	0.3690		
		GARCH(-1)	0.9964	0.0000	0.0000		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH-M(1,2)+tdm	sample ind					
: Z1	M141	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	@SQRT(GARCH)	1.4869	0.0055	0.0028	0.730	0.733
s.e.	1.6216	C	-1.7996	0.0214	0.0090	0.863	0.864
AIC	3.7385	ZHG	0.8672	0.0000	0.0000	0.961	0.959
SBC	3.8979	ZHG*ZHG_TM	-0.2341	0.0000	0.0004	0.951	0.956
J-Bera	0.9907	C	0.0947	0.0000	0.0000	0.983	0.974
		RESID(-1)^2	-0.1310	0.0000	0.0345	0.994	0.989
		RESID(-1)^2*(RESID(-1)<0)	0.1695	0.0004	0.0240	0.987	0.971
		RESID(-2)^2	0.0703	0.0073	0.2092	0.994	0.985
		RESID(-2)^2*(RESID(-2)<0)	-0.1544	0.0010	0.0275		
		GARCH(-1)	1.0073	0.0000	0.0000		

T2ARCH-M(2,2)
M142

Errors generated – model rejected

Fund: ISG*	T2ARCH-M(2,2)+tsq	sample ind					
: Z1	M143	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8800	@SQRT(GARCH)	1.4361	0.0000	0.0001	0.716	0.718
s.e.	1.6115	C	-1.8354	0.0000	0.0001	0.919	0.914
AIC	3.7240	ZHG	0.7255	0.0000	0.0000	0.977	0.979
SBC	3.8993	ZHG^2	-0.0106	0.0000	0.0000	0.977	0.984
J-Bera	0.6686	C	0.1778	0.0000	0.0000	0.993	0.993
		RESID(-1)^2	-0.0724	0.0145	0.0257	0.997	0.997
		RESID(-1)^2*(RESID(-1)<0)	0.2306	0.0000	0.0023	0.984	0.980
		RESID(-2)^2	-0.0152	0.6015	0.6482	0.972	0.967
		RESID(-2)^2*(RESID(-2)<0)	-0.1890	0.0000	0.0183		
		GARCH(-1)	1.2293	0.0000	0.0000		
		GARCH(-2)	-0.2390	0.0000	0.0000		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	T2ARCH-M(2,2)+tdm	sample ind					
: Z1	M144	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8838	@SQRT(GARCH)	13.9599	0.3579	0.1765	0.000	0.000
s.e.	1.5854	C	-21.3315	0.3623	0.1978	0.000	0.000
AIC	3.8101	ZHG	0.8359	0.0000	0.0000	0.000	0.000
SBC	3.9855	ZHG*ZHG_TM	-0.1452	0.0009	0.1044	0.000	0.000
J-Bera	0.0000	C	2.2410	0.0000	0.0000	0.000	0.000
		RESID(-1)^2	-0.0156	0.3823	0.2239	0.000	0.000
		RESID(-1)^2*(RESID(-1)<0)	0.0298	0.3597	0.1400	0.000	0.000
		RESID(-2)^2	0.0044	0.6808	0.5991	0.000	0.000
		RESID(-2)^2*(RESID(-2)<0)	0.0082	0.6361	0.5629		
		GARCH(-1)	-0.0852	0.6555	0.6781		
		GARCH(-2)	0.1374	0.6878	0.5995		

Fund: ISG*	E1GARCH-M(1)	sample ind					
: Z1	M145	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8752	@SQRT(GARCH)	54.6341	0.9578	0.9634	0.314	0.318
s.e.	1.6230	C	-87.4478	0.9577	0.9635	0.212	0.240
AIC	3.8348	ZHG	0.7791	0.0000	0.0000	0.271	0.241
SBC	3.9305	C(4)	0.9390	0.0000	0.0000	0.410	0.391
J-Bera	0.0000	C(5)	0.0012	0.9553	0.9651	0.497	0.532
		C(6)	-0.0051	0.9580	0.9631	0.527	0.604
						0.640	0.706
						0.740	0.803

Fund: ISG*	E1GARCH-M(1)+tsq	sample ind					
: Z1	M146	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8802	@SQRT(GARCH)	5.2542	0.6282	0.6635	0.139	0.143
s.e.	1.5944	C	-8.0985	0.6337	0.6689	0.089	0.114
AIC	3.8031	ZHG	0.7558	0.0000	0.0000	0.072	0.055
SBC	3.9147	ZHG^2	-0.0058	0.0000	0.1463	0.137	0.126
J-Bera	0.6104	C(5)	0.8805	0.0000	0.0000	0.151	0.174
		C(6)	0.0234	0.6622	0.7445	0.129	0.198
		C(7)	-0.0480	0.5886	0.6650	0.193	0.262
						0.198	0.267

Fund: ISG*	E1GARCH-M(1)+tdm	sample ind					
: Z1	M147	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8762	@SQRT(GARCH)	-0.6405	0.5902	0.6307	0.068	0.070
s.e.	1.6208	C	1.2586	0.4944	0.5536	0.134	0.162
AIC	3.8249	ZHG	0.8473	0.0000	0.0000	0.111	0.103
SBC	3.9365	ZHG*ZHG_TM	-0.1376	0.0059	0.1942	0.198	0.236
J-Bera	0.0663	C(5)	0.7867	0.0000	0.0003	0.151	0.198
		C(6)	0.1719	0.1325	0.4512	0.148	0.257
		C(7)	0.0773	0.3878	0.4357	0.216	0.359
						0.275	0.411

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E1GARCH-M(1,1)	sample ind					
: Z1	M148	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8753	@SQRT(GARCH)	33.1648	0.8895	0.8947	0.498	0.482
s.e.	1.6263	C	-53.0793	0.8893	0.8948	0.133	0.109
AIC	3.8438	ZHG	0.7780	0.0000	0.0000	0.203	0.287
SBC	3.9553	C(4)	0.9085	0.0136	0.0770	0.260	0.331
J-Bera	0.0000	C(5)	0.0022	0.8795	0.9087	0.348	0.575
		C(6)	-0.0083	0.8917	0.8906	0.391	0.644
		C(7)	0.0307	0.9354	0.9498	0.490	0.679
						0.036	0.057

Fund: ISG*	E1GARCH-M(1,1)+tsq	sample ind					
: Z1	M149	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8802	@SQRT(GARCH)	3.1728	0.5532	0.4580	0.266	0.270
s.e.	1.5983	C	-4.8303	0.5642	0.4689	0.224	0.257
AIC	3.8108	ZHG	0.7520	0.0000	0.0000	0.125	0.085
SBC	3.9383	ZHG^2	-0.0060	0.0000	0.1417	0.218	0.179
J-Bera	0.6383	C(5)	0.6739	0.0788	0.1521	0.253	0.305
		C(6)	0.0401	0.5703	0.6644	0.226	0.337
		C(7)	-0.0707	0.4969	0.4221	0.317	0.419
		C(8)	0.2122	0.6112	0.6665	0.359	0.464

Fund: ISG*	E1GARCH-M(1,1)+tdm	sample ind					
: Z1	M150	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8786	@SQRT(GARCH)	0.8783	0.0005	0.0456	0.521	0.524
s.e.	1.6088	C	-1.0460	0.0036	0.1416	0.695	0.723
AIC	3.7458	ZHG	0.8597	0.0000	0.0000	0.863	0.791
SBC	3.8733	ZHG*ZHG_TM	-0.1671	0.0013	0.0383	0.935	0.883
J-Bera	0.0770	C(5)	0.0874	0.0000	0.0182	0.949	0.926
		C(6)	-0.0964	0.0000	0.0405	0.918	0.905
		C(7)	-0.0356	0.3470	0.2153	0.696	0.727
		C(8)	0.9772	0.0000	0.0000	0.766	0.769

Fund: ISG*	E1GARCH-M(2,1)	sample ind					
: Z1	M151	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8746	@SQRT(GARCH)	0.3773	0.1830	0.0401	0.044	0.046
s.e.	1.6349	C	-0.6583	0.1208	0.0214	0.122	0.124
AIC	3.8188	ZHG	0.7838	0.0000	0.0000	0.139	0.181
SBC	3.9463	C(4)	1.4662	0.0000	0.0000	0.165	0.244
J-Bera	0.0000	C(5)	0.2849	0.0016	0.0031	0.258	0.347
		C(6)	-0.0282	0.5464	0.4725	0.359	0.604
		C(7)	0.2748	0.0000	0.0000	0.277	0.500
		C(8)	-0.9721	0.0000	0.0000	0.365	0.612

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E1GARCH-M(2,1)+tsq	sample ind					
: Z1	M152	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8837	@SQRT(GARCH)	1.6529	0.0035	0.0331	0.010	0.011
s.e.	1.5785	C	-2.3957	0.0051	0.0422	0.034	0.000
AIC	3.7815	ZHG	0.7577	0.0000	0.0000	0.069	0.753
SBC	3.9249	ZHG^2	-0.0069	0.0000	0.0533	0.116	0.791
J-Bera	0.0000	C(5)	0.7259	0.0000	0.0000	0.192	0.928
		C(6)	0.1431	0.0241	0.0265	0.055	0.034
		C(7)	-0.0527	0.1369	0.0651	0.009	0.002
		C(8)	0.9598	0.0000	0.0000	0.015	0.021
		C(9)	-0.9010	0.0000	0.0000		

Fund: ISG*	E1GARCH-M(2,1)+tdm	sample ind					
: Z1	M153	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8799	@SQRT(GARCH)	0.8985	0.0387	0.0344	0.811	0.812
s.e.	1.6038	C	-1.0439	0.0887	0.1357	0.771	0.783
AIC	3.7500	ZHG	0.8638	0.0000	0.0000	0.895	0.814
SBC	3.8934	ZHG*ZHG_TM	-0.1800	0.0005	0.0251	0.920	0.871
J-Bera	0.0011	C(5)	0.1231	0.0001	0.0490	0.941	0.924
		C(6)	-0.1412	0.0000	0.0861	0.858	0.852
		C(7)	-0.0749	0.1573	0.1921	0.520	0.556
		C(8)	0.4872	0.0000	0.4052	0.556	0.556
		C(9)	0.4814	0.0000	0.4038		

Fund: ISG*	E1GARCH-M(1,2)	sample ind					
: Z1	M154	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8763	@SQRT(GARCH)	5.7793	0.5545	0.6403	0.340	0.339
s.e.	1.6240	C	-9.2679	0.5474	0.6436	0.538	0.548
AIC	3.8450	ZHG	0.7795	0.0000	0.0000	0.650	0.684
SBC	3.9725	C(4)	1.0148	0.0194	0.0013	0.794	0.821
J-Bera	0.0000	C(5)	0.0204	0.6365	0.7211	0.853	0.894
		C(6)	0.0602	0.5761	0.6227	0.829	0.888
		C(7)	-0.0358	0.5913	0.5900	0.899	0.937
		C(8)	-0.1517	0.7458	0.5825	0.698	0.750

Fund: ISG*	E1GARCH-M(1,2)+tsq	sample ind					
: Z1	M155	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8802	@SQRT(GARCH)	2.0757	0.3494	0.3078	0.333	0.338
s.e.	1.6023	C	-3.1226	0.3653	0.3267	0.514	0.542
AIC	3.8165	ZHG	0.7531	0.0000	0.0000	0.357	0.358
SBC	3.9599	ZHG^2	-0.0056	0.0000	0.1768	0.520	0.537
J-Bera	0.6815	C(5)	0.8479	0.0518	0.0618	0.545	0.557
		C(6)	0.0627	0.4939	0.5658	0.578	0.639
		C(7)	0.1286	0.3366	0.3293	0.691	0.748
		C(8)	-0.0907	0.3201	0.2527	0.701	0.732
		C(9)	-0.1144	0.8129	0.7873		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E1GARCH-M(1,2)+tdm	sample ind					
: Z1	M156	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8787	@SQRT(GARCH)	3.0795	0.3825	0.4456	0.287	0.291
s.e.	1.6120	C	-4.6233	0.4041	0.4681	0.428	0.461
AIC	3.8314	ZHG	0.8358	0.0000	0.0000	0.392	0.401
SBC	3.9748	ZHG*ZHG_TM	-0.1371	0.0030	0.1784	0.522	0.531
J-Bera	0.0264	C(5)	0.8953	0.0372	0.0182	0.585	0.634
		C(6)	0.0269	0.6687	0.7351	0.587	0.687
		C(7)	0.0995	0.3858	0.4328	0.687	0.776
		C(8)	-0.0722	0.4041	0.3827	0.755	0.837
		C(9)	-0.0912	0.8421	0.7958		

Fund: ISG*	E1GARCH-M(2,2)	sample ind					
: Z1	M157	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8763	@SQRT(GARCH)	6.2591	0.5849	0.6600	0.357	0.356
s.e.	1.6282	C	-10.0303	0.5790	0.6627	0.544	0.536
AIC	3.8545	ZHG	0.7795	0.0000	0.0000	0.654	0.661
SBC	3.9980	C(4)	1.0070	0.0492	0.0033	0.796	0.801
J-Bera	0.0000	C(5)	0.0186	0.6488	0.7373	0.846	0.880
		C(6)	0.0553	0.6046	0.6447	0.829	0.884
		C(7)	-0.0331	0.6166	0.6159	0.898	0.930
		C(8)	-0.1590	0.7357	0.5847	0.677	0.715
		C(9)	0.0203	0.9504	0.9389		

Fund: ISG*	E1GARCH-M(2,2)+tsq	sample ind					
: Z1	M158	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8778	@SQRT(GARCH)	0.5006	0.3362	0.1969	0.232	0.236
s.e.	1.6219	C	-0.6250	0.4331	0.2973	0.479	0.473
AIC	3.8101	ZHG	0.7687	0.0000	0.0000	0.634	0.631
SBC	3.9695	ZHG^2	-0.0047	0.0010	0.1853	0.741	0.802
J-Bera	0.4883	C(5)	1.5272	0.0002	0.0002	0.672	0.773
		C(6)	0.2668	0.0529	0.0570	0.764	0.859
		C(7)	0.3332	0.0271	0.0027	0.849	0.927
		C(8)	-0.0108	0.8619	0.8184	0.907	0.964
		C(9)	-0.5697	0.0000	0.0001		
		C(10)	-0.6762	0.0000	0.0000		

E1GARCH-M(2,2)+tdm
M159

Errors generated – model rejected

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E2GARCH-M(1)	sample ind					
: Z1	M160	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8753	@SQRT(GARCH)	64.4126	0.9607	0.9689	0.295	0.299
s.e.	1.6265	C	-103.0689	0.9606	0.9689	0.144	0.168
AIC	3.8439	ZHG	0.7793	0.0000	0.0000	0.200	0.174
SBC	3.9554	C(4)	0.9387	0.0000	0.0000	0.316	0.298
J-Bera	0.0000	C(5)	0.0010	0.9590	0.9697	0.397	0.432
		C(6)	-0.0045	0.9609	0.9687	0.429	0.509
		C(7)	0.0007	0.9599	0.9695	0.543	0.613
						0.650	0.723

Fund: ISG*	E2GARCH-M(1)+tsq	sample ind					
: Z1	M161	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8772	@SQRT(GARCH)	-0.3977	0.5490	0.6335	0.280	0.285
s.e.	1.6182	C	0.7638	0.4470	0.5623	0.432	0.459
AIC	3.8075	ZHG	0.7552	0.0000	0.0000	0.372	0.345
SBC	3.9350	ZHG^2	-0.0056	0.0000	0.1806	0.495	0.585
J-Bera	0.7141	C(5)	0.7225	0.0000	0.0001	0.428	0.531
		C(6)	0.2167	0.1059	0.2705	0.453	0.585
		C(7)	-0.0219	0.8169	0.8308	0.569	0.703
		C(8)	-0.1590	0.1557	0.0907	0.637	0.724

Fund: ISG*	E2GARCH-M(1)+tdm	sample ind					
: Z1	M162	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8783	@SQRT(GARCH)	40.9734	0.9364	0.9538	0.107	0.110
s.e.	1.6105	C	-64.5002	0.9366	0.9540	0.032	0.048
AIC	3.8286	ZHG	0.8377	0.0000	0.0000	0.036	0.027
SBC	3.9561	ZHG*ZHG_TM	-0.1346	0.0054	0.1702	0.066	0.059
J-Bera	0.0457	C(5)	0.9133	0.0000	0.0000	0.078	0.089
		C(6)	0.0018	0.9337	0.9554	0.072	0.119
		C(7)	-0.0071	0.9360	0.9539	0.112	0.161
		C(8)	0.0006	0.9330	0.9593	0.152	0.231

Fund: ISG*	E2GARCH-M(1,1)	sample ind					
: Z1	M163	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8755	@SQRT(GARCH)	19.8799	0.8754	0.8386	0.769	0.669
s.e.	1.6289	C	-31.8601	0.8750	0.8393	0.145	0.014
AIC	3.8524	ZHG	0.7776	0.0000	0.0000	0.271	0.260
SBC	3.9799	C(4)	0.8291	0.3081	0.2896	0.249	0.132
J-Bera	0.0000	C(5)	0.0049	0.8661	0.8546	0.359	0.522
		C(6)	-0.0142	0.8779	0.8313	0.458	0.607
		C(7)	0.0039	0.9168	0.8910	0.563	0.560
		C(8)	0.1145	0.8946	0.8799	0.000	0.000

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E2GARCH-M(1,1)+tsq	sample ind					
: Z1	M164	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8772	@SQRT(GARCH)	-0.4245	0.5491	0.6202	0.256	0.261
s.e.	1.6221	C	0.8063	0.4487	0.5507	0.392	0.422
AIC	3.8170	ZHG	0.7558	0.0000	0.0000	0.344	0.316
SBC	3.9604	ZHG^2	-0.0056	0.0001	0.1812	0.468	0.557
J-Bera	0.7079	C(5)	0.7575	0.2054	0.0417	0.401	0.506
		C(6)	0.2131	0.1298	0.2743	0.425	0.561
		C(7)	-0.0179	0.8486	0.8606	0.538	0.682
		C(8)	-0.1570	0.1743	0.0999	0.604	0.701
		C(9)	-0.0362	0.9521	0.9284		

Fund: ISG*	E2GARCH-M(1,1)+tdm	sample ind					
: Z1	M165	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8806	@SQRT(GARCH)	1.1164	0.0000	0.0021	0.675	0.678
s.e.	1.5994	C	-1.3745	0.0001	0.0190	0.835	0.832
AIC	3.7374	ZHG	0.8612	0.0000	0.0000	0.948	0.941
SBC	3.8808	ZHG*ZHG_TM	-0.1870	0.0003	0.0124	0.985	0.989
J-Bera	0.4805	C(5)	0.0924	0.0000	0.0000	0.994	0.994
		C(6)	-0.1001	0.0000	0.0000	0.997	0.995
		C(7)	-0.1941	0.0704	0.0065	0.967	0.962
		C(8)	0.1635	0.1192	0.0098	0.982	0.980
		C(9)	0.9744	0.0000	0.0000		

Fund: ISG*	E2GARCH-M(2,1)	sample ind					
: Z1	M166	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8764	@SQRT(GARCH)	4.9510	0.3572	0.5554	0.859	0.860
s.e.	1.6269	C	-7.9615	0.3474	0.5594	0.861	0.692
AIC	3.8574	ZHG	0.7762	0.0000	0.0000	0.951	0.773
SBC	4.0009	C(4)	0.7865	0.0011	0.0208	0.987	0.966
J-Bera	0.0000	C(5)	0.0332	0.3935	0.5809	0.996	0.989
		C(6)	-0.0452	0.4142	0.5020	0.995	0.822
		C(7)	0.0175	0.6530	0.6677	0.001	0.000
		C(8)	0.5925	0.1017	0.1052	0.002	0.000
		C(9)	-0.4562	0.0994	0.1461		

Fund: ISG*	E2GARCH-M(2,1)+tsq	sample ind					
: Z1	M167	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8779	@SQRT(GARCH)	0.1784	0.6286	0.5188	0.534	0.538
s.e.	1.6212	C	-0.1826	0.7366	0.6791	0.742	0.739
AIC	3.7911	ZHG	0.7521	0.0000	0.0000	0.889	0.944
SBC	3.9504	ZHG^2	-0.0044	0.0009	0.2191	0.959	0.985
J-Bera	0.7426	C(5)	1.0585	0.0002	0.0000	0.986	0.999
		C(6)	0.3704	0.0073	0.0011	0.995	1.000
		C(7)	-0.0549	0.4821	0.4814	0.992	0.998
		C(8)	-0.1319	0.2252	0.0980	0.966	0.985
		C(9)	0.2685	0.0291	0.0000		
		C(10)	-0.7948	0.0000	0.0000		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	E2GARCH-M(2,1)+tdm	sample ind					
: Z1	M168	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8826	@SQRT(GARCH)	2.1415	0.0014	0.1232	0.081	0.084
s.e.	1.5897	C	-3.0997	0.0034	0.1546	0.212	0.005
AIC	3.8220	ZHG	0.8546	0.0000	0.0000	0.370	0.137
SBC	3.9814	ZHG*ZHG_TM	-0.1648	0.0001	0.1225	0.529	0.221
J-Bera	0.0000	C(5)	0.7946	0.0000	0.0000	0.667	0.333
		C(6)	0.1029	0.0350	0.0499	0.188	0.001
		C(7)	-0.0536	0.1074	0.0912	0.000	0.000
		C(8)	0.0212	0.5272	0.5352	0.000	0.000
		C(9)	0.9576	0.0000	0.0000		
		C(10)	-0.8940	0.0000	0.0000		

Fund: ISG*	E2GARCH-M(1,2)	sample ind					
: Z1	M169	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8763	@SQRT(GARCH)	4.5488	0.4662	0.5553	0.486	0.467
s.e.	1.6276	C	-7.3108	0.4549	0.5606	0.603	0.522
AIC	3.8539	ZHG	0.7808	0.0000	0.0000	0.738	0.742
SBC	3.9974	C(4)	1.1320	0.0461	0.0013	0.859	0.843
J-Bera	0.0000	C(5)	0.0263	0.6173	0.6736	0.891	0.894
		C(6)	0.0763	0.4946	0.5234	0.892	0.910
		C(7)	-0.0444	0.5213	0.4893	0.937	0.937
		C(8)	-0.0132	0.7962	0.7312	0.139	0.105
		C(9)	-0.2939	0.6364	0.3733		

Fund: ISG*	E2GARCH-M(1,2)+tsq	sample ind					
: Z1	M170	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8799	@SQRT(GARCH)	1.3500	0.2327	0.1701	0.572	0.574
s.e.	1.6080	C	-1.9808	0.2568	0.1960	0.808	0.817
AIC	3.8194	ZHG	0.7463	0.0000	0.0000	0.533	0.542
SBC	3.9788	ZHG^2	-0.0062	0.0000	0.1245	0.700	0.708
J-Bera	0.7475	C(5)	1.0578	0.0197	0.0120	0.750	0.715
		C(6)	0.0829	0.4934	0.5291	0.784	0.786
		C(7)	0.2120	0.1611	0.1057	0.864	0.869
		C(8)	-0.1377	0.1558	0.1012	0.852	0.836
		C(9)	-0.1093	0.3458	0.1869		
		C(10)	-0.4446	0.3726	0.1760		

Fund: ISG*	E2GARCH-M(1,2)+tdm	sample ind					
: Z1	M171	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8786	@SQRT(GARCH)	2.0169	0.2494	0.2714	0.434	0.433
s.e.	1.6168	C	-2.9337	0.2847	0.3087	0.641	0.645
AIC	3.8370	ZHG	0.8384	0.0000	0.0000	0.585	0.605
SBC	3.9964	ZHG*ZHG_TM	-0.1471	0.0011	0.1479	0.696	0.685
J-Bera	0.0240	C(5)	1.1399	0.0135	0.0076	0.754	0.810
		C(6)	0.0387	0.6728	0.7051	0.757	0.834
		C(7)	0.1573	0.2247	0.2059	0.844	0.898
		C(8)	-0.1023	0.2468	0.2110	0.735	0.776
		C(9)	-0.0665	0.4895	0.3674		
		C(10)	-0.4202	0.3999	0.2247		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

E2GARCH-M(2,2)
M172

Errors generated – model rejected

E2GARCH-M(2,2)+tsq
M173

Errors generated – model rejected

E2GARCH-M(2,2)+tdm
M174

Errors generated – model rejected

P1ARCH-M(1)
M175

Errors generated – model rejected

Fund: ISG*	P1ARCH-M(1)+tsq	sample ind					
: Z1	M176	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8781	@SQRT(GARCH)	0.0653	0.9499	0.9108	0.849	0.850
s.e.	1.6123	C	0.0123	0.9938	0.9890	0.931	0.936
AIC	3.7951	ZHG	0.7691	0.0000	0.0000	0.532	0.506
SBC	3.9226	ZHG^2	-0.0055	0.0000	0.1494	0.621	0.580
J-Bera	0.7742	C(5)	73.6084	0.9119	0.7958	0.622	0.583
		C(6)	0.0030	0.9340	0.8533	0.645	0.632
		C(7)	-0.0520	0.8402	0.7370	0.739	0.734
		C(8)	10.6725	0.6314	0.2487	0.760	0.726

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P1ARCH-M(1)+tdm	sample ind					
: Z1	M177	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8755	@SQRT(GARCH)	-0.0140	0.9885	0.9790	0.848	0.849
s.e.	1.6290	C	0.2663	0.8568	0.7462	0.923	0.927
AIC	3.8064	ZHG	0.8586	0.0000	0.0000	0.606	0.585
SBC	3.9339	ZHG*ZHG_TM	-0.1456	0.0035	0.1216	0.739	0.711
J-Bera	0.1539	C(5)	102.1823	0.9155	0.8108	0.737	0.711
		C(6)	0.0019	0.9381	0.8604	0.673	0.674
		C(7)	-0.0892	0.7672	0.4988	0.769	0.781
		C(8)	11.3440	0.6216	0.2473	0.831	0.821

P1ARCH-M(1,1)
M178

Errors generated – model rejected

Fund: ISG*	P1ARCH-M(1,1)+tsq	sample ind					
: Z1	M179	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8801	@SQRT(GARCH)	1.0946	0.1794	0.2331	0.438	0.441
s.e.	1.6027	C	-1.4617	0.2331	0.0000	0.691	0.723
AIC	3.7596	ZHG	0.7492	0.0000	0.0000	0.558	0.528
SBC	3.9031	ZHG^2	-0.0085	0.0000		0.519	0.514
J-Bera	0.7074	C(5)	1.1393	0.3671	0.5266	0.663	0.647
		C(6)	-0.0038	0.5266	0.4254	0.718	0.695
		C(7)	-0.1309	0.4254	0.0000	0.767	0.733
		C(8)	0.9118	0.0000	0.0021	0.491	0.438
		C(9)	5.4290	0.0021			

Fund: ISG*	P1ARCH-M(1,1)+tdm	sample ind					
: Z1	M180	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8755	@SQRT(GARCH)	0.8707	0.1665	0.2721	0.961	0.961
s.e.	1.6331	C	-1.0011	0.2721	0.0000	0.865	0.866
AIC	3.7653	ZHG	0.8472	0.0000	0.0010	0.959	0.919
SBC	3.9088	ZHG*ZHG_TM	-0.1925	0.0010		0.984	0.968
J-Bera	0.2081	C(5)	0.4741	0.1748	0.0000	0.983	0.977
		C(6)	-0.0037	0.0000	0.1647	0.965	0.954
		C(7)	-0.0724	0.1647	0.0000	0.876	0.869
		C(8)	0.9993	0.0000	0.0000	0.911	0.901
		C(9)	5.7801	0.0000			

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P1ARCH-M(2,1)	sample ind					
: Z1	M181	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8724	@SQRT(GARCH)	0.6957	0.1495	0.2771	0.415	0.419
s.e.	1.6536	C	-1.1275	0.1346	0.2457	0.705	0.724
AIC	3.8100	ZHG	0.7689	0.0000	0.0000	0.873	0.853
SBC	3.9534	C(4)	0.1952	0.5702	0.5034	0.945	0.933
J-Bera	0.0001	C(5)	-0.0043	0.8584	0.8292	0.964	0.956
		C(6)	-0.1503	0.0206	0.1557	0.953	0.954
		C(7)	0.6418	0.3424	0.5852	0.969	0.974
		C(8)	0.3533	0.5994	0.7653	0.986	0.988
		C(9)	4.9214	0.3711	0.2710		

Fund: ISG*	P1ARCH-M(2,1)+tsq	sample ind					
: Z1	M182	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8781	@SQRT(GARCH)	0.6528	0.4639	0.5288	0.747	0.749
s.e.	1.6197	C	-0.8409	0.5288	0.0000	0.949	0.957
AIC	3.8009	ZHG	0.7459	0.0000	0.0000	0.680	0.686
SBC	3.9603	ZHG^2	-0.0066	0.0000		0.581	0.607
J-Bera	0.8571	C(5)	5.2296	0.9833	0.9873	0.708	0.743
		C(6)	-0.0000	0.9873	0.9828	0.789	0.808
		C(7)	0.3425	0.9828	0.9743	0.729	0.713
		C(8)	0.7134	0.9743	0.9956	0.595	0.583
		C(9)	0.0977	0.9956	0.9028		
		C(10)	8.4366	0.9028			

P1ARCH-M(2,1)+tdm
M183

Errors generated – model rejected

P1ARCH-M(1,2)
M184

Errors generated – model rejected

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P1ARCH-M(1,2)+tsq	sample ind					
: Z1	M185	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8796	@SQRT(GARCH)	1.0294	0.3017	0.0132	0.798	0.800
s.e.	1.6098	C	-1.4271	0.3620	0.0210	0.867	0.864
AIC	3.7867	ZHG	0.7454	0.0000	0.0000	0.643	0.644
SBC	3.9461	ZHG^2	-0.0075	0.0000	0.0381	0.504	0.489
J-Bera	0.8531	C(5)	1.2759	0.6767	0.4111	0.625	0.657
		C(6)	0.0274	0.7552	0.4948	0.745	0.774
		C(7)	0.0244	0.9076	0.8236	0.701	0.669
		C(8)	-0.0342	0.7649	0.5109	0.635	0.622
		C(9)	0.7763	0.0001	0.0002		
		C(10)	3.7515	0.3761	0.1656		

Fund: ISG*	P1ARCH-M(1,2)+tdm	sample ind					
: Z1	M186	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8755	@SQRT(GARCH)	1.3504	0.0644	0.1221	0.814	0.815
s.e.	1.6373	C	-1.7006	0.1221	0.0000	0.926	0.924
AIC	3.7817	ZHG	0.8511	0.0000	0.0001	0.921	0.922
SBC	3.9411	ZHG*ZHG_TM	-0.1873	0.0001		0.757	0.755
J-Bera	0.5255	C(5)	0.5411	0.0916	0.2106	0.865	0.845
		C(6)	0.0016	0.2106	0.5964	0.922	0.907
		C(7)	0.4096	0.5964	0.5788	0.931	0.902
		C(8)	-0.0116	0.5788	0.0000	0.807	0.797
		C(9)	0.9487	0.0000	0.0379		
		C(10)	4.5346	0.0379			

P1ARCH-M(2,2)
M187

Errors generated – model rejected

Fund: ISG*	P1ARCH-M(2,2)+tsq	sample ind					
: Z1	M188	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8802	@SQRT(GARCH)	0.9936	0.2643	0.0000	0.872	0.873
s.e.	1.6103	C	-1.3478	0.3222	0.0000	0.656	0.665
AIC	3.8007	ZHG	0.7370	0.0000	0.0000	0.393	0.348
SBC	3.9761	ZHG^2	-0.0076	0.0000	0.0290	0.544	0.503
J-Bera	0.8381	C(5)	1.7162	0.1007	0.3047	0.622	0.711
		C(6)	0.0373	0.6951	0.5727	0.665	0.773
		C(7)	0.4008	0.7061	0.4431	0.697	0.758
		C(8)	-0.0446	0.4716	0.5241	0.744	0.787
		C(9)	0.6648	0.0717	0.1005		
		C(10)	-0.1217	0.7045	0.6927		
		C(11)	3.0925	0.0495	0.0930		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P1ARCH-M(2,2)+tdm	sample ind					
: Z1	M189	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8784	@SQRT(GARCH)	1.5430	0.2700	0.2741	0.656	0.659
s.e.	1.6221	C	-2.0641	0.3471	0.3387	0.718	0.724
AIC	3.8121	ZHG	0.8574	0.0000	0.0000	0.703	0.721
SBC	3.9874	ZHG*ZHG_TM	-0.1912	0.0000	0.0558	0.507	0.500
J-Bera	0.6837	C(5)	1.8167	0.7169	0.6217	0.652	0.618
		C(6)	0.0017	0.7169	0.6941	0.766	0.732
		C(7)	0.3756	0.8614	0.8328	0.665	0.577
		C(8)	-0.0073	0.8228	0.7981	0.663	0.602
		C(9)	0.8590	0.0001	0.4912		
		C(10)	-0.0673	0.6964	0.9489		
		C(11)	4.8243	0.3554	0.3230		

P2ARCH-M(1,2)
M190

Errors generated – model rejected

Fund: ISG*	P2ARCH-M(1,2)+tsq	sample ind					
: Z1	M191	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8794	@SQRT(GARCH)	0.8933	0.2195	0.0027	0.990	0.990
s.e.	1.6154	C	-1.2210	0.2768	0.0033	0.980	0.980
AIC	3.7948	ZHG	0.7411	0.0000	0.0000	0.470	0.472
SBC	3.9701	ZHG^2	-0.0077	0.0000	0.0387	0.452	0.454
J-Bera	0.8033	C(5)	1.0895	0.5800	0.2723	0.582	0.617
		C(6)	0.0091	0.8988	0.8817	0.704	0.733
		C(7)	0.3671	0.8814	0.9050	0.655	0.619
		C(8)	-0.0156	0.8378	0.8071	0.657	0.628
		C(9)	-0.2012	0.8299	0.9082		
		C(10)	0.7706	0.0002	0.0000		
		C(11)	3.4514	0.2640	0.0972		

Fund: ISG*	P2ARCH-M(1,2)+tdm	sample ind					
: Z1	M192	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8764	@SQRT(GARCH)	1.3857	0.0793	0.2035	0.750	0.752
s.e.	1.6352	C	-1.7247	0.1467	0.2727	0.692	0.697
AIC	3.7999	ZHG	0.8570	0.0000	0.0000	0.713	0.716
SBC	3.9752	ZHG*ZHG_TM	-0.1978	0.0001	0.0074	0.609	0.594
J-Bera	0.4222	C(5)	0.7797	0.2043	0.3682	0.746	0.695
		C(6)	0.0017	0.8440	0.7379	0.830	0.789
		C(7)	0.3524	0.8512	0.7523	0.832	0.760
		C(8)	-0.0089	0.6895	0.6185	0.699	0.645
		C(9)	0.0142	0.9483	0.9300		
		C(10)	0.9287	0.0000	0.0000		
		C(11)	5.0168	0.0413	0.0811		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	P2ARCH-M(2,2)	sample ind					
: Z1	M193	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8725	@SQRT(GARCH)	0.8785	0.2399	0.4070	0.452	0.456
s.e.	1.6610	C	-1.3992	0.2347	0.3938	0.753	0.770
AIC	3.8539	ZHG	0.7695	0.0000	0.0000	0.857	0.850
SBC	4.0292	C(4)	0.0414	0.0000	0.6462	0.768	0.776
J-Bera	0.0116	C(5)	0.0132	0.7528	0.8256	0.868	0.868
		C(6)	0.2165	0.9482	0.9552	0.926	0.925
		C(7)	-0.0086	0.7855	0.8665	0.922	0.922
		C(8)	0.9387	0.4376	0.6586	0.921	0.914
		C(9)	0.8399	0.4541	0.7552		
		C(10)	0.1171	0.9159	0.9642		
		C(11)	0.2310	0.7673	0.8290		

Fund: ISG*	P2ARCH-M(2,2)+tsq	sample ind					
: Z1	M194	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8798	@SQRT(GARCH)	1.0028	0.2912	0.0050	0.554	0.557
s.e.	1.6167	C	-1.3743	0.3491	0.0069	0.633	0.659
AIC	3.8206	ZHG	0.7451	0.0000	0.0000	0.302	0.256
SBC	4.0119	ZHG^2	-0.0076	0.0000	0.0190	0.399	0.377
J-Bera	0.8158	C(5)	1.7018	0.4517	0.3467	0.485	0.545
		C(6)	0.0218	0.8267	0.7283	0.581	0.665
		C(7)	0.3915	0.8114	0.7587	0.639	0.678
		C(8)	-0.0174	0.8663	0.8701	0.692	0.712
		C(9)	-0.3255	0.8683	0.9070		
		C(10)	0.6675	0.2597	0.1742		
		C(11)	-0.1098	0.8180	0.7573		
		C(12)	3.1245	0.2631	0.1099		

P2ARCH-M(2,2)+tdm
M195

Errors generated – model rejected

Fund: ISG*	COMP	sample ind					
: Z1	M196	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8716	C	0.0198	0.8370	0.8157	0.978	0.978
s.e.	1.6502	ZHG	0.7615	0.0000	0.0000	0.999	1.000
AIC	3.7297	C(3)	2.2992	0.0000	0.0000	0.748	0.757
SBC	3.8413	C(4)	0.9603	0.0000	0.0000	0.843	0.852
J-Bera	0.9006	C(5)	-0.0652	0.0000	0.0019	0.528	0.560
		C(6)	0.0514	0.4384	0.3526	0.655	0.691
		C(7)	0.2674	0.7719	0.7061	0.631	0.659
						0.631	0.597

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

COMP+tsq
M197

Errors generated – model rejected

Fund: ISG*	COMP+tdm	sample ind					
: Z1	M198	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8749	C	0.2532	0.0513	0.0677	0.748	0.750
s.e.	1.6330	ZHG	0.8273	0.0000	0.0000	0.907	0.908
AIC	3.7207	ZHG*ZHG_TM	-0.1498	0.0006	0.0293	0.534	0.552
SBC	3.8482	C(4)	2.1519	0.0000	0.0000	0.632	0.640
J-Bera	0.9752	C(5)	0.9548	0.0000	0.0000	0.494	0.517
		C(6)	-0.0669	0.0000	0.0010	0.622	0.656
		C(7)	0.0597	0.4146	0.3619	0.494	0.473
		C(8)	0.0834	0.9326	0.9192	0.445	0.393

Fund: ISG*	ASCO	sample ind					
: Z1	M199	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8720	C	-0.0164	0.8660	0.8500	0.764	0.766
s.e.	1.6521	ZHG	0.7652	0.0000	0.0000	0.718	0.730
AIC	3.7424	C(3)	2.2352	0.0000	0.0000	0.541	0.533
SBC	3.8699	C(4)	0.9614	0.0000	0.0000	0.675	0.673
J-Bera	0.9380	C(5)	-0.0604	0.0000	0.0020	0.528	0.491
		C(6)	0.1215	0.2483	0.3128	0.656	0.626
		C(7)	-0.1021	0.3054	0.4748	0.620	0.540
		C(8)	-0.4043	0.4729	0.4045	0.598	0.454

Fund: ISG*	ASCO+tsq	sample ind					
: Z1	M200	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8777	C	0.1216	0.2485	0.1822	0.908	0.909
s.e.	1.6185	ZHG	0.7514	0.0000	0.0000	0.965	0.968
AIC	3.7214	ZHG^2	-0.0058	0.0000	0.0379	0.506	0.514
SBC	3.8648	C(4)	2.2030	0.0000	0.0000	0.651	0.671
J-Bera	0.6095	C(5)	0.9477	0.0000	0.0000	0.432	0.453
		C(6)	-0.0740	0.0000	0.0004	0.554	0.596
		C(7)	0.0942	0.3725	0.2823	0.413	0.416
		C(8)	-0.0687	0.5492	0.5613	0.304	0.239
		C(9)	-0.4079	0.5995	0.4376		

Table B-1: ISG* Candidate Models With 'Best' GARCH(1,1) Highlighted (continued)

Fund: ISG*	ASCO+tdm	sample ind					
: Z1	M201	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8753	C	0.2595	0.0411	0.0017	0.686	0.689
s.e.	1.6342	ZHG	0.8340	0.0000	0.0000	0.760	0.774
AIC	3.7310	ZHG*ZHG_TM	-0.1476	0.0000	0.0000	0.413	0.407
SBC	3.8745	C(4)	2.1847	0.0000	0.0000	0.523	0.537
J-Bera	0.9235	C(5)	0.9531	0.0000	0.0000	0.464	0.450
		C(6)	-0.0640	0.0000	0.0013	0.592	0.578
		C(7)	0.0734	0.4397	0.4662	0.466	0.395
		C(8)	-0.0594	0.5300	0.6500	0.397	0.269
		C(9)	-0.4628	0.6015	0.5320		

SWE* Scottish Widows Ethical Model Output

The model selected as 'best' was EGARCH(2,2) with asymmetry of order 2 and with a significant Henriksson and Merton (1981) timing term in the mean equation as per equation (2) on p.63. Again, Table B-2 below provides summary output for all 201 candidate models in model set M1 described in Appendix A: Key To Model Sets on p.210, including the 'best' which is highlighted by shading (listed 78th in Table B-2).

Again, some models fail to converge or otherwise generate errors during estimation and are thus excluded from consideration as a candidate 'best' model.

In Table B-2 "ZHG" again refers to the Hoare Govett smallet companies index, the benchmark for SWE*, so that this coefficient is the estimated 'beta'.

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted

Fund: SWE*	plain OLS	sample ind					
Z20	M1	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7871	C	-0.0579	0.6725	0.6376	0.009	0.009
s.e.	1.9389	ZHG	0.7352	0.0000	0.0000	0.025	0.013
AIC	4.1721					0.026	0.020
SBC	4.2049					0.042	0.044
J-Bera	0.0002					0.033	0.032
						0.002	0.009
						0.002	0.016
						0.004	0.024

Fund: SWE*	OLS+tsq	sample ind					
Z20	M2	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7875	C	-0.0072	0.9640	0.9604	0.016	0.014
s.e.	1.9419	ZHG	0.7305	0.0000	0.0000	0.041	0.021
AIC	4.1800	ZHG^2	-0.0020	0.5319	0.6338	0.038	0.029
SBC	4.2293					0.055	0.059
J-Bera	0.0001					0.046	0.046
						0.004	0.015
						0.004	0.023
						0.008	0.037

Fund: SWE*	OLS+tdm	sample ind					
Z20	M3	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7886	C	0.1281	0.5364	0.5025	0.024	0.022
s.e.	1.9368	ZHG	0.7794	0.0000	0.0000	0.058	0.031
AIC	4.1748	ZHG*ZHG_TM	-0.0985	0.2323	0.3158	0.051	0.041
SBC	4.2241					0.070	0.079
J-Bera	0.0001					0.070	0.074
						0.009	0.026
						0.009	0.038
						0.016	0.061

Fund: SWE*	ARCH(1)	sample ind					
Z20	M4	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0822	0.5160	0.5430	0.538	0.538
s.e.	1.9491	ZHG	0.7295	0.0000	0.0000	0.679	0.645
AIC	4.1517	C	3.0403	0.0000	0.0000	0.234	0.248
SBC	4.2175	RESID(-1)^2	0.1753	0.0156	0.1889	0.349	0.409
J-Bera	0.0759					0.407	0.498
						0.227	0.372
						0.200	0.342
						0.248	0.492

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	ARCH(1)+tsq	sample ind					
Z20	M5	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7874	C	-0.0372	0.8114	0.7999	0.611	0.609
s.e.	1.9522	ZHG	0.7252	0.0000	0.0000	0.726	0.693
AIC	4.1600	ZHG^2	-0.0017	0.4909	0.6382	0.232	0.243
SBC	4.2422	C	3.0246	0.0000	0.0000	0.331	0.390
J-Bera	0.0638	RESID(-1)^2	0.1795	0.0141	0.1828	0.389	0.479
						0.259	0.405
						0.228	0.373
						0.276	0.541

Fund: SWE*	ARCH(1)+tdm	sample ind					
Z20	M6	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7885	C	0.0972	0.6515	0.5886	0.680	0.678
s.e.	1.9471	ZHG	0.7721	0.0000	0.0000	0.751	0.724
AIC	4.1545	ZHG*ZHG_TM	-0.0950	0.1928	0.2799	0.241	0.252
SBC	4.2366	C	2.9878	0.0000	0.0000	0.333	0.390
J-Bera	0.0482	RESID(-1)^2	0.1874	0.0121	0.1705	0.409	0.499
						0.330	0.477
						0.288	0.438
						0.346	0.625

Fund: SWE*	GARCH(1,1)	sample ind					
Z20	M7	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0832	0.5123	0.5378	0.556	0.556
s.e.	1.9542	ZHG	0.7290	0.0000	0.0000	0.710	0.677
AIC	4.1616	C	3.1257	0.0094	0.0048	0.244	0.256
SBC	4.2438	RESID(-1)^2	0.1774	0.0155	0.1846	0.362	0.420
J-Bera	0.0752	GARCH(-1)	-0.0239	0.9386	0.9299	0.422	0.509
						0.237	0.381
						0.206	0.346
						0.254	0.498

Fund: SWE*	GARCH(1,1)+tsq	sample ind					
Z20	M8	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7874	C	-0.0372	0.8150	0.7992	0.611	0.609
s.e.	1.9572	ZHG	0.7252	0.0000	0.0000	0.726	0.693
AIC	4.1700	ZHG^2	-0.0017	0.5071	0.6385	0.232	0.243
SBC	4.2686	C	3.0244	0.0084	0.0081	0.331	0.390
J-Bera	0.0638	RESID(-1)^2	0.1795	0.0143	0.1840	0.389	0.479
		GARCH(-1)	0.0001	0.9998	0.9998	0.259	0.405
						0.228	0.373
						0.275	0.541

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	GARCH(1,1)+tdm	sample ind					
Z20	M9	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7885	C	0.0975	0.6593	0.5859	0.677	0.675
s.e.	1.9521	ZHG	0.7722	0.0000	0.0000	0.748	0.720
AIC	4.1644	ZHG*ZHG_TM	-0.0951	0.2067	0.2799	0.240	0.251
SBC	4.2630	C	2.9789	0.0053	0.0067	0.331	0.389
J-Bera	0.0483	RESID(-1)^2	0.1870	0.0124	0.1720	0.407	0.498
		GARCH(-1)	0.0026	0.9926	0.9926	0.329	0.476
						0.287	0.437
						0.345	0.624

Fund: SWE*	GARCH(2,1)	sample ind					
Z20	M10	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7868	C	-0.0628	0.6271	0.6417	0.700	0.698
s.e.	1.9598	ZHG	0.7229	0.0000	0.0000	0.890	0.867
AIC	4.1636	C	3.7516	0.0017	0.0150	0.635	0.633
SBC	4.2622	RESID(-1)^2	0.1842	0.0127	0.1636	0.788	0.823
J-Bera	0.1235	GARCH(-1)	-0.0018	0.9943	0.9936	0.851	0.883
		GARCH(-2)	-0.1908	0.1870	0.5078	0.591	0.672
						0.488	0.557
						0.536	0.708

Fund: SWE*	GARCH(2,1)+tsq	sample ind					
Z20	M11	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7873	C	-0.0072	0.9651	0.9608	0.740	0.737
s.e.	1.9626	ZHG	0.7197	0.0000	0.0000	0.857	0.833
AIC	4.1715	ZHG^2	-0.0022	0.4238	0.5583	0.581	0.581
SBC	4.2865	C	3.3847	0.0010	0.0214	0.736	0.780
J-Bera	0.1043	RESID(-1)^2	0.1839	0.0135	0.1625	0.802	0.850
		GARCH(-1)	0.0943	0.7518	0.7195	0.630	0.716
		GARCH(-2)	-0.1922	0.2075	0.4779	0.547	0.619
						0.591	0.780

Fund: SWE*	GARCH(2,1)+tdm	sample ind					
Z20	M12	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7885	C	0.1289	0.5722	0.4621	0.790	0.788
s.e.	1.9574	ZHG	0.7707	0.0000	0.0000	0.856	0.837
AIC	4.1660	ZHG*ZHG_TM	-0.1015	0.1908	0.2362	0.589	0.593
SBC	4.2810	C	3.2711	0.0008	0.0183	0.737	0.784
J-Bera	0.0760	RESID(-1)^2	0.1913	0.0119	0.1500	0.818	0.867
		GARCH(-1)	0.1083	0.7069	0.6749	0.716	0.793
		GARCH(-2)	-0.1858	0.2091	0.4712	0.628	0.698
						0.675	0.854

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	GARCH(1,2)	sample ind					
Z20	M13	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7861	C	-0.1831	0.0836	0.1273	0.372	0.373
s.e.	1.9632	ZHG	0.7290	0.0000	0.0000	0.515	0.519
AIC	4.1555	C	2.5674	0.0664	0.0774	0.627	0.615
SBC	4.2541	RESID(-1)^2	0.1257	0.0340	0.2884	0.769	0.781
J-Bera	0.1163	RESID(-2)^2	-0.1060	0.0289	0.0429	0.729	0.720
		GARCH(-1)	0.2774	0.5035	0.5503	0.423	0.472
						0.372	0.487
						0.439	0.534

Fund: SWE*	GARCH(1,2)+tsq	sample ind					
Z20	M14	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7868	C	-0.0977	0.4652	0.4975	0.437	0.437
s.e.	1.9649	ZHG	0.7223	0.0000	0.0000	0.539	0.541
AIC	4.1635	ZHG^2	-0.0023	0.3794	0.5115	0.628	0.613
SBC	4.2786	C	2.2647	0.0324	0.0953	0.749	0.764
J-Bera	0.0834	RESID(-1)^2	0.1247	0.0316	0.2996	0.701	0.685
		RESID(-2)^2	-0.1143	0.0055	0.0324	0.486	0.513
		GARCH(-1)	0.3659	0.2646	0.3925	0.468	0.558
						0.539	0.611

Fund: SWE*	GARCH(1,2)+tdm	sample ind					
Z20	M15	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7881	C	0.0897	0.6572	0.6110	0.559	0.559
s.e.	1.9592	ZHG	0.7812	0.0000	0.0000	0.696	0.690
AIC	4.1573	ZHG*ZHG_TM	-0.1206	0.1005	0.1423	0.673	0.656
SBC	4.2723	C	2.0624	0.0381	0.1641	0.771	0.792
J-Bera	0.0598	RESID(-1)^2	0.1412	0.0246	0.2632	0.769	0.766
		RESID(-2)^2	-0.1205	0.0097	0.0746	0.650	0.672
		GARCH(-1)	0.4061	0.1989	0.3865	0.634	0.706
						0.698	0.770

Fund: SWE*	GARCH(2,2)	sample ind					
Z20	M16	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7865	C	-0.1338	0.2750	0.2849	0.407	0.406
s.e.	1.9663	ZHG	0.7234	0.0000	0.0000	0.517	0.521
AIC	4.1631	C	3.0413	0.0589	0.4513	0.691	0.691
SBC	4.2781	RESID(-1)^2	0.1244	0.0334	0.2693	0.829	0.840
J-Bera	0.1514	RESID(-2)^2	-0.0980	0.0182	0.3320	0.831	0.834
		GARCH(-1)	0.2840	0.3944	0.7070	0.540	0.584
		GARCH(-2)	-0.1406	0.5299	0.7974	0.461	0.568
						0.525	0.609

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	GARCH(2,2)+tsq	sample ind					
Z20	M17	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0463	0.7559	0.7502	0.490	0.489
s.e.	1.9692	ZHG	0.7157	0.0000	0.0000	0.567	0.566
AIC	4.1709	ZHG^2	-0.0026	0.3184	0.4363	0.703	0.699
SBC	4.3024	C	2.6562	0.0335	0.4624	0.822	0.837
J-Bera	0.1055	RESID(-1)^2	0.1236	0.0349	0.2830	0.813	0.811
		RESID(-2)^2	-0.1056	0.0050	0.2629	0.630	0.652
		GARCH(-1)	0.3723	0.1953	0.5954	0.587	0.665
		GARCH(-2)	-0.1231	0.4999	0.8016	0.640	0.709

Fund: SWE*	GARCH(2,2)+tdm	sample ind					
Z20	M18	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7881	C	0.1209	0.5683	0.4878	0.590	0.590
s.e.	1.9639	ZHG	0.7785	0.0000	0.0000	0.689	0.683
AIC	4.1646	ZHG*ZHG_TM	-0.1229	0.0996	0.1265	0.777	0.769
SBC	4.2961	C	2.4659	0.0407	0.4911	0.869	0.883
J-Bera	0.0765	RESID(-1)^2	0.1368	0.0286	0.2629	0.882	0.884
		RESID(-2)^2	-0.1099	0.0100	0.3081	0.782	0.794
		GARCH(-1)	0.3971	0.1699	0.5981	0.746	0.797
		GARCH(-2)	-0.1102	0.5067	0.8074	0.787	0.844

Fund: SWE*	T1ARCH(1)	sample ind					
Z20	M19	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1275	0.3416	0.3316	0.801	0.799
s.e.	1.9552	ZHG	0.7295	0.0000	0.0000	0.929	0.916
AIC	4.1532	C	3.0727	0.0000	0.0000	0.218	0.219
SBC	4.2354	RESID(-1)^2	0.0639	0.4583	0.4388	0.339	0.383
J-Bera	0.0960	RESID(-1)^2*(RESID(-1)<0)	0.2156	0.1832	0.3057	0.441	0.503
						0.324	0.455
						0.308	0.424
						0.351	0.592

Fund: SWE*	T1ARCH(1)+tsq	sample ind					
Z20	M20	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7871	C	-0.0892	0.6044	0.5353	0.864	0.862
s.e.	1.9584	ZHG	0.7259	0.0000	0.0000	0.942	0.932
AIC	4.1619	ZHG^2	-0.0015	0.5703	0.6966	0.218	0.215
SBC	4.2605	C	3.0549	0.0000	0.0000	0.328	0.367
J-Bera	0.0864	RESID(-1)^2	0.0698	0.4298	0.4244	0.429	0.490
		RESID(-1)^2*(RESID(-1)<0)	0.2144	0.2009	0.3245	0.357	0.478
						0.334	0.445
						0.374	0.625

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T1ARCH(1)+tdm	sample ind					
Z20	M21	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7883	C	0.0404	0.8629	0.8220	0.926	0.924
s.e.	1.9533	ZHG	0.7695	0.0000	0.0000	0.942	0.935
AIC	4.1566	ZHG*ZHG_TM	-0.0893	0.2337	0.3197	0.228	0.222
SBC	4.2552	C	3.0129	0.0000	0.0000	0.331	0.367
J-Bera	0.0722	RESID(-1)^2	0.0788	0.3684	0.3959	0.442	0.501
		RESID(-1)^2*(RESID(-1)<0)	0.2171	0.2034	0.3361	0.425	0.536
						0.392	0.500
						0.436	0.692

Fund: SWE*	T1ARCH(1,1)	sample ind					
Z20	M22	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1362	0.3203	0.2963	0.492	0.490
s.e.	1.9603	ZHG	0.7347	0.0000	0.0000	0.639	0.615
AIC	4.1582	C	2.3052	0.0516	0.0767	0.119	0.131
SBC	4.2568	RESID(-1)^2	0.0014	0.9849	0.9816	0.204	0.254
J-Bera	0.1050	RESID(-1)^2*(RESID(-1)<0)	0.2689	0.0806	0.2033	0.265	0.350
		GARCH(-1)	0.2376	0.4847	0.5483	0.187	0.331
						0.219	0.373
						0.262	0.514

Fund: SWE*	T1ARCH(1,1)+tsq	sample ind					
Z20	M23	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0592	0.7224	0.6828	0.381	0.378
s.e.	1.9641	ZHG	0.7310	0.0000	0.0000	0.525	0.496
AIC	4.1637	ZHG^2	-0.0030	0.2392	0.4038	0.091	0.103
SBC	4.2788	C	1.9666	0.0445	0.1508	0.150	0.203
J-Bera	0.1106	RESID(-1)^2	-0.0267	0.6691	0.5782	0.183	0.271
		RESID(-1)^2*(RESID(-1)<0)	0.2798	0.0401	0.1995	0.165	0.310
		GARCH(-1)	0.3502	0.2245	0.4185	0.215	0.387
						0.250	0.511

Fund: SWE*	T1ARCH(1,1)+tdm	sample ind					
Z20	M24	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7882	C	0.0793	0.7303	0.6509	0.386	0.383
s.e.	1.9587	ZHG	0.7899	0.0000	0.0000	0.519	0.494
AIC	4.1576	ZHG*ZHG_TM	-0.1158	0.1346	0.1595	0.098	0.113
SBC	4.2726	C	1.9649	0.0410	0.1476	0.159	0.217
J-Bera	0.1129	RESID(-1)^2	-0.0251	0.6822	0.6059	0.205	0.302
		RESID(-1)^2*(RESID(-1)<0)	0.2883	0.0382	0.1973	0.207	0.362
		GARCH(-1)	0.3438	0.2233	0.4270	0.262	0.442
						0.307	0.573

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T1ARCH(2,1)	sample ind					
Z20	M25	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7858	C	-0.0662	0.6009	0.5882	0.553	0.541
s.e.	1.9695	ZHG	0.7061	0.0000	0.0000	0.839	0.870
AIC	4.1346	C	4.7809	0.0000	0.0000	0.806	0.817
SBC	4.2497	RESID(-1)^2	0.0441	0.5495	0.3394	0.912	0.949
J-Bera	0.3124	RESID(-1)^2*(RESID(-1)<0)	0.2179	0.0242	0.0041	0.963	0.983
		GARCH(-1)	0.1153	0.5872	0.3943	0.822	0.864
		GARCH(-2)	-0.5165	0.0102	0.0097	0.616	0.647
						0.675	0.872

Fund: SWE*	T1ARCH(2,1)+tsq	sample ind					
Z20	M26	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.0397	0.8101	0.7759	0.067	0.067
s.e.	1.9703	ZHG	0.7235	0.0000	0.0000	0.165	0.151
AIC	4.1681	ZHG^2	-0.0038	0.1460	0.2579	0.068	0.078
SBC	4.2996	C	1.4787	0.0074	0.0401	0.116	0.154
J-Bera	0.1065	RESID(-1)^2	-0.0696	0.0724	0.0202	0.087	0.128
		RESID(-1)^2*(RESID(-1)<0)	0.2177	0.0121	0.1789	0.055	0.141
		GARCH(-1)	0.8412	0.0083	0.0233	0.087	0.208
		GARCH(-2)	-0.2846	0.2373	0.2451	0.105	0.300

Fund: SWE*	T1ARCH(2,1)+tdm	sample ind					
Z20	M27	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7880	C	0.1107	0.6232	0.5033	0.056	0.056
s.e.	1.9645	ZHG	0.7910	0.0000	0.0000	0.144	0.134
AIC	4.1615	ZHG*ZHG_TM	-0.1329	0.0900	0.0790	0.075	0.088
SBC	4.2929	C	1.4535	0.0058	0.0327	0.125	0.170
J-Bera	0.1072	RESID(-1)^2	-0.0702	0.0650	0.0145	0.108	0.155
		RESID(-1)^2*(RESID(-1)<0)	0.2163	0.0110	0.1754	0.077	0.175
		GARCH(-1)	0.8634	0.0053	0.0139	0.117	0.253
		GARCH(-2)	-0.2996	0.2072	0.1832	0.144	0.355

Fund: SWE*	T1ARCH(1,2)	sample ind					
Z20	M28	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7866	C	-0.1482	0.2580	0.1888	0.559	0.558
s.e.	1.9659	ZHG	0.7345	0.0000	0.0000	0.808	0.800
AIC	4.1400	C	2.1286	0.0083	0.1469	0.595	0.591
SBC	4.2551	RESID(-1)^2	0.0389	0.6482	0.5624	0.755	0.780
J-Bera	0.1719	RESID(-1)^2*(RESID(-1)<0)	0.2018	0.1480	0.2786	0.762	0.774
		RESID(-2)^2	-0.0792	0.0465	0.0343	0.520	0.600
		GARCH(-1)	0.3417	0.1764	0.4664	0.555	0.645
						0.590	0.709

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T1ARCH(1,2)+tsq	sample ind					
Z20	M29	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7865	C	-0.0969	0.5424	0.4534	0.578	0.576
s.e.	1.9717	ZHG	0.7237	0.0000	0.0000	0.832	0.824
AIC	4.1446	ZHG^2	-0.0032	0.2021	0.3513	0.581	0.579
SBC	4.2761	C	1.9931	0.0051	0.1604	0.728	0.768
J-Bera	0.1504	RESID(-1)^2	0.0274	0.7477	0.6503	0.718	0.745
		RESID(-1)^2*(RESID(-1)<0)	0.2253	0.1161	0.2255	0.594	0.666
		RESID(-2)^2	-0.0791	0.0426	0.0256	0.641	0.723
		GARCH(-1)	0.3891	0.0825	0.3892	0.649	0.780

Fund: SWE*	T1ARCH(1,2)+tdm	sample ind					
Z20	M30	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7875	C	0.0593	0.7722	0.7132	0.581	0.580
s.e.	1.9671	ZHG	0.7877	0.0000	0.0000	0.844	0.840
AIC	4.1384	ZHG*ZHG_TM	-0.1296	0.0722	0.0942	0.613	0.613
SBC	4.2699	C	1.7996	0.0077	0.1598	0.753	0.795
J-Bera	0.1306	RESID(-1)^2	0.0235	0.7767	0.6983	0.770	0.801
		RESID(-1)^2*(RESID(-1)<0)	0.2567	0.0887	0.1588	0.694	0.759
		RESID(-2)^2	-0.0809	0.0540	0.0331	0.747	0.816
		GARCH(-1)	0.4360	0.0379	0.2925	0.751	0.853

Fund: SWE*	T1ARCH(2,2)	sample ind					
Z20	M31	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1217	0.3246	0.2916	0.610	0.608
s.e.	1.9705	ZHG	0.7261	0.0000	0.0000	0.868	0.869
AIC	4.1468	C	2.6133	0.0080	0.0303	0.672	0.675
SBC	4.2783	RESID(-1)^2	0.0315	0.7150	0.6007	0.816	0.846
J-Bera	0.2439	RESID(-1)^2*(RESID(-1)<0)	0.2195	0.1353	0.2158	0.848	0.869
		RESID(-2)^2	-0.0607	0.3138	0.1279	0.620	0.692
		GARCH(-1)	0.3533	0.1792	0.3230	0.628	0.694
		GARCH(-2)	-0.1630	0.4501	0.5622	0.666	0.790

Fund: SWE*	T1ARCH(2,2)+tsq	sample ind					
Z20	M32	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7863	C	-0.0994	0.5215	0.4444	0.647	0.644
s.e.	1.9774	ZHG	0.7179	0.0000	0.0000	0.882	0.886
AIC	4.1519	ZHG^2	-0.0031	0.2260	0.3392	0.652	0.659
SBC	4.2998	C	2.2395	0.0032	0.0482	0.798	0.841
J-Bera	0.2167	RESID(-1)^2	0.0244	0.7765	0.6642	0.806	0.839
		RESID(-1)^2*(RESID(-1)<0)	0.2524	0.1084	0.1713	0.666	0.735
		RESID(-2)^2	-0.0699	0.1863	0.0757	0.699	0.764
		GARCH(-1)	0.4219	0.1182	0.2534	0.697	0.829
		GARCH(-2)	-0.1138	0.6088	0.6675		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T1ARCH(2,2)+tdm	sample ind					
Z20	M33	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7876	C	0.0756	0.7362	0.6406	0.623	0.620
s.e.	1.9715	ZHG	0.7833	0.0000	0.0000	0.869	0.876
AIC	4.1460	ZHG*ZHG_TM	-0.1289	0.0908	0.0813	0.699	0.707
SBC	4.2939	C	2.1508	0.0034	0.0578	0.831	0.872
J-Bera	0.2152	RESID(-1)^2	0.0273	0.7477	0.6345	0.850	0.881
		RESID(-1)^2*(RESID(-1)<0)	0.2476	0.1099	0.1807	0.773	0.828
		RESID(-2)^2	-0.0727	0.1385	0.0709	0.803	0.856
		GARCH(-1)	0.4442	0.0843	0.2457	0.802	0.901
		GARCH(-2)	-0.1140	0.5930	0.6662		

Fund: SWE*	T2ARCH(1)	sample ind					
Z20	M34	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1269	0.3440	0.3338	0.675	0.672
s.e.	1.9603	ZHG	0.7283	0.0000	0.0000	0.680	0.658
AIC	4.1596	C	2.9640	0.0000	0.0000	0.143	0.147
SBC	4.2582	RESID(-1)^2	0.0536	0.5534	0.5441	0.239	0.278
J-Bera	0.0857	RESID(-1)^2*(RESID(-1)<0)	0.2293	0.1630	0.2761	0.319	0.394
		RESID(-2)^2*(RESID(-2)<0)	0.0778	0.5508	0.4290	0.206	0.338
						0.210	0.326

Fund: SWE*	T2ARCH(1)+tsq	sample ind					
Z20	M35	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7871	C	-0.0819	0.6292	0.5658	0.740	0.735
s.e.	1.9635	ZHG	0.7238	0.0000	0.0000	0.687	0.664
AIC	4.1678	ZHG^2	-0.0017	0.5111	0.6421	0.141	0.138
SBC	4.2829	C	2.9303	0.0000	0.0000	0.225	0.255
J-Bera	0.0818	RESID(-1)^2	0.0615	0.4968	0.5130	0.302	0.370
		RESID(-1)^2*(RESID(-1)<0)	0.2274	0.1757	0.2985	0.227	0.352
		RESID(-2)^2*(RESID(-2)<0)	0.0858	0.5101	0.4255	0.228	0.339

Fund: SWE*	T2ARCH(1)+tdm	sample ind					
Z20	M36	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7882	C	0.0538	0.8201	0.7589	0.785	0.780
s.e.	1.9584	ZHG	0.7710	0.0000	0.0000	0.672	0.651
AIC	4.1619	ZHG*ZHG_TM	-0.0963	0.2231	0.2734	0.143	0.139
SBC	4.2770	C	2.8732	0.0000	0.0000	0.223	0.249
J-Bera	0.0766	RESID(-1)^2	0.0720	0.4208	0.4705	0.306	0.370
		RESID(-1)^2*(RESID(-1)<0)	0.2293	0.1787	0.3114	0.273	0.394
		RESID(-2)^2*(RESID(-2)<0)	0.0958	0.4699	0.4200	0.269	0.380
						0.313	0.585

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH(1,1)	sample ind					
Z20	M37	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7857	C	-0.1578	0.2419	0.1750	0.798	0.799
s.e.	1.9701	ZHG	0.7122	0.0000	0.0000	0.951	0.945
AIC	4.0948	C	0.0839	0.0140	0.0176	0.281	0.297
SBC	4.2098	RESID(-1)^2	-0.0519	0.0079	0.0258	0.429	0.473
J-Bera	0.6912	RESID(-1)^2*(RESID(-1)<0)	0.2267	0.1658	0.1054	0.455	0.505
		RESID(-2)^2*(RESID(-2)<0)	-0.2344	0.1644	0.0918	0.380	0.488
		GARCH(-1)	1.0266	0.0000	0.0000	0.464	0.559

Fund: SWE*	T2ARCH(1,1)+tsq	sample ind					
Z20	M38	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7871	C	0.0157	0.9226	0.9087	0.901	0.901
s.e.	1.9686	ZHG	0.7181	0.0000	0.0000	0.973	0.969
AIC	4.1116	ZHG^2	-0.0015	0.5196	0.5471	0.306	0.322
SBC	4.2431	C	0.1037	0.0102	0.0080	0.460	0.506
J-Bera	0.7616	RESID(-1)^2	-0.0552	0.0000	0.0083	0.415	0.466
		RESID(-1)^2*(RESID(-1)<0)	0.2396	0.0000	0.0751	0.407	0.495
		RESID(-2)^2*(RESID(-2)<0)	-0.2436	0.0000	0.0663	0.469	0.549
		GARCH(-1)	1.0209	0.0000	0.0000	0.564	0.645

Fund: SWE*	T2ARCH(1,1)+tdm	sample ind					
Z20	M39	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	0.0398	0.8426	0.8097	0.879	0.880
s.e.	1.9690	ZHG	0.7521	0.0000	0.0000	0.988	0.984
AIC	4.0921	ZHG*ZHG_TM	-0.0984	0.1432	0.1319	0.361	0.375
SBC	4.2236	C	0.1111	0.0034	0.0117	0.520	0.567
J-Bera	0.7941	RESID(-1)^2	-0.0610	0.0050	0.0107	0.516	0.560
		RESID(-1)^2*(RESID(-1)<0)	0.2232	0.2004	0.0944	0.439	0.527
		RESID(-2)^2*(RESID(-2)<0)	-0.2340	0.1918	0.0737	0.497	0.556
		GARCH(-1)	1.0268	0.0000	0.0000	0.582	0.644

Fund: SWE*	T2ARCH(2,1)	sample ind					
Z20	M40	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7864	C	-0.1615	0.2079	0.1545	0.518	0.519
s.e.	1.9721	ZHG	0.7278	0.0000	0.0000	0.666	0.684
AIC	4.1481	C	1.9582	0.0126	0.0272	0.556	0.559
SBC	4.2796	RESID(-1)^2	-0.0356	0.3421	0.0406	0.638	0.648
J-Bera	0.2456	RESID(-1)^2*(RESID(-1)<0)	0.3245	0.0416	0.0648	0.659	0.652
		RESID(-2)^2*(RESID(-2)<0)	-0.1948	0.1261	0.1224	0.511	0.585
		GARCH(-1)	0.7485	0.0015	0.0063	0.598	0.667
		GARCH(-2)	-0.3142	0.0851	0.1278	0.658	0.709

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH(2,1)+tsq	sample ind					
Z20	M41	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7855	C	-0.0151	0.9233	0.9106	0.618	0.617
s.e.	1.9812	ZHG	0.7191	0.0000	0.0000	0.751	0.764
AIC	4.1481	ZHG^2	-0.0055	0.0287	0.0705	0.628	0.639
SBC	4.2960	C	1.6146	0.0021	0.0070	0.770	0.800
J-Bera	0.2876	RESID(-1)^2	-0.0425	0.1729	0.0019	0.709	0.714
		RESID(-1)^2*(RESID(-1)<0)	0.3296	0.0357	0.0377	0.682	0.723
		RESID(-2)^2*(RESID(-2)<0)	-0.2183	0.0559	0.0134	0.783	0.813
		GARCH(-1)	0.8786	0.0000	0.0000	0.785	0.810
		GARCH(-2)	-0.3365	0.0628	0.0254		

Fund: SWE*	T2ARCH(2,1)+tdm	sample ind					
Z20	M42	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7874	C	0.1610	0.4453	0.3115	0.571	0.571
s.e.	1.9725	ZHG	0.8059	0.0000	0.0000	0.769	0.787
AIC	4.1418	ZHG*ZHG_TM	-0.1652	0.0223	0.0155	0.640	0.649
SBC	4.2897	C	1.6222	0.0062	0.0092	0.775	0.800
J-Bera	0.3131	RESID(-1)^2	-0.0415	0.2200	0.0032	0.763	0.775
		RESID(-1)^2*(RESID(-1)<0)	0.3372	0.0387	0.0394	0.757	0.797
		RESID(-2)^2*(RESID(-2)<0)	-0.2213	0.0709	0.0157	0.844	0.872
		GARCH(-1)	0.8659	0.0000	0.0004	0.845	0.866
		GARCH(-2)	-0.3325	0.0817	0.0345		

Fund: SWE*	T2ARCH(1,2)	sample ind					
Z20	M43	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1419	0.2701	0.2069	0.494	0.493
s.e.	1.9707	ZHG	0.7337	0.0000	0.0000	0.785	0.773
AIC	4.1496	C	2.1288	0.0348	0.2975	0.558	0.554
SBC	4.2811	RESID(-1)^2	0.0349	0.6908	0.6115	0.723	0.747
J-Bera	0.1605	RESID(-1)^2*(RESID(-1)<0)	0.1991	0.1655	0.3481	0.722	0.742
		RESID(-2)^2	-0.0799	0.0738	0.0483	0.465	0.558
		RESID(-2)^2*(RESID(-2)<0)	0.0251	0.8556	0.8792	0.506	0.608
		GARCH(-1)	0.3351	0.3126	0.6148	0.544	0.687

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH(1,2)+tsq	sample ind					
Z20	M44	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7865	C	-0.1191	0.4387	0.3470	0.583	0.582
s.e.	1.9768	ZHG	0.7269	0.0000	0.0000	0.832	0.823
AIC	4.1546	ZHG^2	-0.0027	0.2823	0.4281	0.632	0.629
SBC	4.3025	C	1.8983	0.0153	0.3040	0.780	0.811
J-Bera	0.1472	RESID(-1)^2	0.0368	0.6856	0.5725	0.753	0.772
		RESID(-1)^2*(RESID(-1)<0)	0.2181	0.1581	0.3347	0.595	0.663
		RESID(-2)^2	-0.0857	0.0526	0.0408	0.647	0.723
		RESID(-2)^2*(RESID(-2)<0)	0.0037	0.9787	0.9821	0.658	0.771
		GARCH(-1)	0.4188	0.1088	0.4755		

Fund: SWE*	T2ARCH(1,2)+tdm	sample ind					
Z20	M45	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7874	C	0.0430	0.8400	0.7895	0.701	0.699
s.e.	1.9723	ZHG	0.7841	0.0000	0.0000	0.911	0.907
AIC	4.1479	ZHG*ZHG_TM	-0.1235	0.0933	0.1122	0.623	0.625
SBC	4.2958	C	1.8863	0.0172	0.2802	0.763	0.806
J-Bera	0.1360	RESID(-1)^2	0.0342	0.6910	0.5946	0.797	0.829
		RESID(-1)^2*(RESID(-1)<0)	0.2706	0.1203	0.2337	0.721	0.783
		RESID(-2)^2	-0.0833	0.0492	0.0358	0.763	0.826
		RESID(-2)^2*(RESID(-2)<0)	-0.0072	0.9618	0.9692	0.763	0.866
		GARCH(-1)	0.4049	0.1280	0.4796		

Fund: SWE*	T2ARCH(2,2)	sample ind					
Z20	M46	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7868	C	-0.1175	0.3822	0.3074	0.688	0.687
s.e.	1.9753	ZHG	0.7277	0.0000	0.0000	0.880	0.878
AIC	4.1571	C	2.4077	0.0308	0.2767	0.712	0.718
SBC	4.3050	RESID(-1)^2	0.0395	0.6665	0.5717	0.841	0.867
J-Bera	0.2308	RESID(-1)^2*(RESID(-1)<0)	0.2231	0.1769	0.2714	0.864	0.876
		RESID(-2)^2	-0.0689	0.2119	0.1425	0.636	0.700
		RESID(-2)^2*(RESID(-2)<0)	-0.0185	0.9098	0.9251	0.668	0.724
		GARCH(-1)	0.4032	0.2487	0.5286	0.696	0.781
		GARCH(-2)	-0.1355	0.4926	0.6509		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH(2,2)+tsq	sample ind					
Z20	M47	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7866	C	-0.1015	0.4994	0.4331	0.727	0.725
s.e.	1.9812	ZHG	0.7227	0.0000	0.0000	0.875	0.875
AIC	4.1611	ZHG^2	-0.0027	0.2724	0.3968	0.700	0.711
SBC	4.3255	C	2.1963	0.0172	0.2588	0.839	0.877
J-Bera	0.2353	RESID(-1)^2	0.0292	0.7351	0.6465	0.845	0.867
		RESID(-1)^2*(RESID(-1)<0)	0.2509	0.1342	0.2376	0.718	0.769
		RESID(-2)^2	-0.0688	0.2482	0.0730	0.754	0.802
		RESID(-2)^2*(RESID(-2)<0)	-0.0352	0.8264	0.8622	0.756	0.846
		GARCH(-1)	0.4503	0.1737	0.4699		
		GARCH(-2)	-0.1199	0.5698	0.6442		

Fund: SWE*	T2ARCH(2,2)+tdm	sample ind					
Z20	M48	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7876	C	0.1443	0.5060	0.3670	0.697	0.696
s.e.	1.9765	ZHG	0.8003	0.0000	0.0000	0.820	0.831
AIC	4.1514	ZHG*ZHG_TM	-0.1542	0.0357	0.0261	0.672	0.682
SBC	4.3157	C	1.7332	0.0261	0.0247	0.814	0.846
J-Bera	0.2865	RESID(-1)^2	-0.0256	0.6605	0.5007	0.824	0.838
		RESID(-1)^2*(RESID(-1)<0)	0.3378	0.0498	0.0567	0.811	0.844
		RESID(-2)^2	-0.0168	0.7575	0.6503	0.881	0.904
		RESID(-2)^2*(RESID(-2)<0)	-0.1959	0.2445	0.0851	0.880	0.903
		GARCH(-1)	0.7620	0.0334	0.0110		
		GARCH(-2)	-0.2714	0.2629	0.1580		

Fund: SWE*	E1GARCH(1)	sample ind					
Z20	M49	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7865	C	-0.1506	0.2710	0.2481	0.586	0.583
s.e.	1.9563	ZHG	0.7284	0.0000	0.0000	0.857	0.840
AIC	4.1615	C(3)	1.0974	0.0000	0.0000	0.201	0.201
SBC	4.2436	C(4)	0.2445	0.0305	0.2388	0.315	0.361
J-Bera	0.0712	C(5)	-0.1583	0.0877	0.1488	0.377	0.433
						0.285	0.405
						0.298	0.424

Fund: SWE*	E1GARCH(1)+tsq	sample ind					
Z20	M50	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.1039	0.5506	0.4726	0.593	0.587
s.e.	1.9589	ZHG	0.7269	0.0000	0.0000	0.861	0.842
AIC	4.1708	ZHG^2	-0.0012	0.6305	0.7510	0.203	0.199
SBC	4.2694	C(4)	1.1037	0.0000	0.0000	0.308	0.354
J-Bera	0.0645	C(5)	0.2344	0.0362	0.2627	0.364	0.419
		C(6)	-0.1608	0.0875	0.1473	0.309	0.420
						0.326	0.448
						0.374	0.594

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E1GARCH(1)+tdm	sample ind					
Z20	M51	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7881	C	0.0163	0.9454	0.9284	0.641	0.634
s.e.	1.9538	ZHG	0.7681	0.0000	0.0000	0.886	0.871
		ZHG*ZHG_T					
AIC	4.1655	M	-0.0830	0.2605	0.3613	0.221	0.214
SBC	4.2641	C(4)	1.0949	0.0000	0.0000	0.319	0.366
J-Bera	0.0512	C(5)	0.2403	0.0330	0.2502	0.391	0.451
		C(6)	-0.1646	0.0845	0.1381	0.384	0.487
						0.398	0.513
						0.451	0.670

Fund: SWE*	E1GARCH(1,1)	sample ind					
Z20	M52	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7864	C	-0.1614	0.2429	0.2144	0.459	0.458
s.e.	1.9616	ZHG	0.7319	0.0000	0.0000	0.658	0.637
AIC	4.1644	C(3)	0.7316	0.0868	0.1789	0.126	0.140
SBC	4.2630	C(4)	0.2121	0.0619	0.2885	0.214	0.266
J-Bera	0.0823	C(5)	-0.1995	0.0303	0.0801	0.248	0.330
		C(6)	0.2989	0.3791	0.4796	0.168	0.309
						0.215	0.373
						0.261	0.501

Fund: SWE*	E1GARCH(1,1)+tsq	sample ind					
Z20	M53	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7869	C	-0.0839	0.6240	0.5610	0.385	0.383
s.e.	1.9644	ZHG	0.7305	0.0000	0.0000	0.573	0.546
AIC	4.1707	ZHG^2	-0.0026	0.3008	0.4730	0.110	0.123
SBC	4.2858	C(4)	0.6728	0.0696	0.2100	0.177	0.233
J-Bera	0.0855	C(5)	0.1697	0.1139	0.3993	0.190	0.274
		C(6)	-0.2151	0.0149	0.0716	0.166	0.305
		C(7)	0.3672	0.2136	0.3929	0.227	0.392
						0.273	0.514

Fund: SWE*	E1GARCH(1,1)+tdm	sample ind					
Z20	M54	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7880	C	0.0577	0.8068	0.7415	0.416	0.413
s.e.	1.9594	ZHG	0.7884	0.0000	0.0000	0.587	0.564
		ZHG*ZHG_T					
AIC	4.1638	M	-0.1134	0.1388	0.1775	0.122	0.136
SBC	4.2789	C(4)	0.6559	0.0682	0.2115	0.188	0.250
J-Bera	0.0888	C(5)	0.1813	0.0908	0.3707	0.216	0.311
		C(6)	-0.2200	0.0135	0.0632	0.219	0.368
		C(7)	0.3702	0.1929	0.3842	0.292	0.463
						0.348	0.588

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E1GARCH(2,1)	sample ind					
Z20	M55	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7852	C	-0.1621	0.2050	0.2052	0.953	0.953
s.e.	1.9723	ZHG	0.7068	0.0000	0.0000	0.984	0.977
AIC	4.1419	C(3)	1.4881	0.0000	0.0000	0.606	0.593
SBC	4.2569	C(4)	0.3974	0.0085	0.0015	0.762	0.805
J-Bera	0.2829	C(5)	-0.1793	0.0602	0.0287	0.852	0.885
		C(6)	0.2435	0.0403	0.0391	0.822	0.884
		C(7)	-0.6681	0.0000	0.0002	0.502	0.496
						0.600	0.810

Fund: SWE*	E1GARCH(2,1)+tsq	sample ind					
Z20	M56	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7869	C	-0.0253	0.8668	0.8457	0.326	0.326
s.e.	1.9697	ZHG	0.7106	0.0000	0.0000	0.411	0.451
AIC	4.1003	ZHG^2	-0.0020	0.4338	0.5018	0.509	0.574
SBC	4.2318	C(4)	0.6670	0.0000	0.0000	0.676	0.738
J-Bera	0.2990	C(5)	-0.0226	0.5763	0.7077	0.273	0.281
		C(6)	-0.0452	0.1391	0.0433	0.285	0.326
		C(7)	1.4299	0.0000	0.0000	0.310	0.264
		C(8)	-0.9773	0.0000	0.0000	0.279	0.272

Fund: SWE*	E1GARCH(2,1)+tdm	sample ind					
Z20	M57	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7880	C	0.1049	0.6151	0.4821	0.306	0.305
s.e.	1.9646	ZHG	0.7607	0.0000	0.0000	0.385	0.433
AIC	4.0943	ZHG*ZHG_TM	-0.1008	0.1737	0.1559	0.500	0.572
SBC	4.2258	C(4)	0.6600	0.0000	0.0000	0.668	0.740
J-Bera	0.3299	C(5)	-0.0182	0.6460	0.7487	0.350	0.363
		C(6)	-0.0424	0.1486	0.0614	0.395	0.431
		C(7)	1.4306	0.0000	0.0000	0.393	0.326
		C(8)	-0.9772	0.0000	0.0000	0.360	0.333

Fund: SWE*	E1GARCH(1,2)	sample ind					
Z20	M58	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7864	C	-0.1663	0.2469	0.2020	0.492	0.492
s.e.	1.9669	ZHG	0.7370	0.0000	0.0000	0.779	0.772
AIC	4.1671	C(3)	0.6140	0.1065	0.2810	0.240	0.241
SBC	4.2821	C(4)	0.2240	0.0443	0.2818	0.378	0.408
J-Bera	0.0445	C(5)	-0.1791	0.2307	0.4372	0.401	0.422
		C(6)	-0.1753	0.0614	0.1060	0.245	0.352
		C(7)	0.4866	0.1043	0.3466	0.320	0.443
						0.365	0.518

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E1GARCH(1,2)+tsq	sample ind					
Z20	M59	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7868	C	-0.0906	0.5059	0.5286	0.339	0.342
s.e.	1.9700	ZHG	0.7169	0.0000	0.0000	0.541	0.510
AIC	4.1159	ZHG^2	-0.0018	0.4877	0.5482	0.169	0.194
SBC	4.2474	C(4)	0.1125	0.0478	0.0695	0.252	0.325
J-Bera	0.7320	C(5)	0.0857	0.4760	0.6853	0.328	0.425
		C(6)	-0.1897	0.0856	0.4251	0.210	0.366
		C(7)	-0.0347	0.0987	0.1481	0.291	0.433
		C(8)	0.9703	0.0000	0.0000	0.372	0.530

Fund: SWE*	E1GARCH(1,2)+tdm	sample ind					
Z20	M60	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7877	C	-0.0058	0.9746	0.9738	0.489	0.491
s.e.	1.9661	ZHG	0.7586	0.0000	0.0000	0.773	0.754
AIC	4.1050	ZHG*ZHG_T M	-0.0820	0.2432	0.2693	0.237	0.253
SBC	4.2365	C(4)	0.1128	0.0979	0.1028	0.340	0.404
J-Bera	0.7558	C(5)	0.0831	0.5379	0.6696	0.457	0.530
		C(6)	-0.1927	0.1228	0.3893	0.369	0.509
		C(7)	-0.0464	0.0513	0.1730	0.463	0.564
		C(8)	0.9741	0.0000	0.0000	0.562	0.660

Fund: SWE*	E1GARCH(2,2)	sample ind					
Z20	M61	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7861	C	-0.1767	0.1770	0.1805	0.647	0.646
s.e.	1.9734	ZHG	0.7246	0.0000	0.0000	0.677	0.687
AIC	4.1567	C(3)	0.9482	0.0000	0.1253	0.553	0.567
SBC	4.2882	C(4)	0.2674	0.0373	0.1456	0.672	0.706
J-Bera	0.1187	C(5)	-0.3125	0.0527	0.1299	0.741	0.742
		C(6)	-0.1388	0.1168	0.2241	0.536	0.612
		C(7)	0.7353	0.0007	0.0534	0.624	0.684
		C(8)	-0.4698	0.0175	0.2637	0.677	0.720

Fund: SWE*	E1GARCH(2,2)+tsq	sample ind					
Z20	M62	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7865	C	-0.0901	0.5886	0.5335	0.614	0.611
s.e.	1.9767	ZHG	0.7214	0.0000	0.0000	0.664	0.675
AIC	4.1614	ZHG^2	-0.0032	0.1975	0.3695	0.524	0.543
SBC	4.3093	C(4)	0.8852	0.0000	0.1086	0.688	0.737
J-Bera	0.1188	C(5)	0.2441	0.0521	0.2009	0.713	0.722
		C(6)	-0.3098	0.0502	0.1167	0.627	0.681
		C(7)	-0.1506	0.0873	0.1922	0.732	0.765
		C(8)	0.8003	0.0004	0.0326	0.754	0.777
		C(9)	-0.4754	0.0422	0.1993		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E1GARCH(2,2)+tdm	sample ind					
Z20	M63	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7877	C	0.0778	0.7290	0.6524	0.661	0.657
s.e.	1.9711	ZHG	0.7895	0.0000	0.0000	0.717	0.728
AIC	4.1531	ZHG*ZHG_T M	-0.1309	0.0731	0.1068	0.566	0.581
SBC	4.3010	C(4)	0.8488	0.0001	0.0995	0.729	0.778
J-Bera	0.1391	C(5)	0.2635	0.0376	0.1670	0.770	0.787
		C(6)	-0.3179	0.0428	0.1209	0.731	0.775
		C(7)	-0.1567	0.0801	0.1648	0.824	0.846
		C(8)	0.8106	0.0002	0.0353	0.835	0.844
		C(9)	-0.4680	0.0433	0.1769		

Fund: SWE*	E2GARCH(1)	sample ind					
Z20	M64	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7864	C	-0.1572	0.2643	0.2268	0.421	0.417
s.e.	1.9618	ZHG	0.7277	0.0000	0.0000	0.649	0.621
AIC	4.1595	C(3)	1.1217	0.0000	0.0000	0.142	0.147
SBC	4.2581	C(4)	0.2050	0.0915	0.3102	0.238	0.281
J-Bera	0.0415	C(5)	-0.1756	0.0705	0.1131	0.275	0.345
		C(6)	-0.1613	0.0984	0.1670	0.135	0.253
						0.168	0.296
						0.212	0.427

Fund: SWE*	E2GARCH(1)+tsq	sample ind					
Z20	M65	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0875	0.6101	0.5432	0.411	0.402
s.e.	1.9642	ZHG	0.7234	0.0000	0.0000	0.637	0.604
AIC	4.1668	ZHG^2	-0.0022	0.3661	0.5635	0.135	0.132
SBC	4.2819	C(4)	1.1308	0.0000	0.0000	0.215	0.254
J-Bera	0.0499	C(5)	0.1881	0.1182	0.3577	0.240	0.307
		C(6)	-0.1822	0.0612	0.1031	0.159	0.275
		C(7)	-0.1770	0.0735	0.1296	0.199	0.327
						0.242	0.466

Fund: SWE*	E2GARCH(1)+tdm	sample ind					
Z20	M66	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7880	C	0.0558	0.8090	0.7543	0.443	0.431
s.e.	1.9594	ZHG	0.7795	0.0000	0.0000	0.661	0.633
AIC	4.1592	ZHG*ZHG_T M	-0.1105	0.1314	0.2163	0.146	0.141
SBC	4.2742	C(4)	1.1151	0.0000	0.0000	0.222	0.262
J-Bera	0.0563	C(5)	0.2014	0.0954	0.3209	0.263	0.333
		C(6)	-0.1858	0.0604	0.0924	0.218	0.339
		C(7)	-0.1897	0.0552	0.1059	0.267	0.398
						0.318	0.546

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E2GARCH(1,1)	sample ind					
Z20	M67	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7864	C	-0.1622	0.2478	0.2113	0.433	0.429
s.e.	1.9669	ZHG	0.7292	0.0000	0.0000	0.639	0.613
AIC	4.1690	C(3)	0.9930	0.1009	0.1127	0.140	0.148
SBC	4.2840	C(4)	0.2143	0.0827	0.2903	0.236	0.281
J-Bera	0.0484	C(5)	-0.1783	0.0659	0.1075	0.272	0.348
		C(6)	-0.1376	0.2587	0.3409	0.137	0.260
		C(7)	0.0939	0.8334	0.8537	0.176	0.311
						0.221	0.440

Fund: SWE*	E2GARCH(1,1)+tsq	sample ind					
Z20	M68	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7869	C	-0.0888	0.6057	0.5350	0.414	0.408
s.e.	1.9695	ZHG	0.7262	0.0000	0.0000	0.609	0.577
AIC	4.1757	ZHG^2	-0.0025	0.3191	0.5100	0.130	0.133
SBC	4.3072	C(4)	0.9448	0.0516	0.2018	0.208	0.254
J-Bera	0.0650	C(5)	0.1948	0.1051	0.3487	0.228	0.305
		C(6)	-0.1879	0.0489	0.0973	0.161	0.289
		C(7)	-0.1411	0.2252	0.3673	0.213	0.357
		C(8)	0.1397	0.6960	0.8179	0.259	0.489

Fund: SWE*	E2GARCH(1,1)+tdm	sample ind					
Z20	M69	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7880	C	0.0582	0.8037	0.7390	0.449	0.441
s.e.	1.9647	ZHG	0.7848	0.0000	0.0000	0.630	0.604
AIC	4.1679	ZHG*ZHG_TM	-0.1152	0.1260	0.1851	0.142	0.145
SBC	4.2994	C(4)	0.9250	0.0353	0.1986	0.218	0.268
J-Bera	0.0750	C(5)	0.2098	0.0803	0.3111	0.256	0.340
		C(6)	-0.1915	0.0481	0.0876	0.221	0.358
		C(7)	-0.1510	0.1787	0.3277	0.285	0.435
		C(8)	0.1417	0.6576	0.8112	0.340	0.572

Fund: SWE*	E2GARCH(2,1)	sample ind					
Z20	M70	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7845	C	-0.1609	0.2063	0.2068	0.934	0.932
s.e.	1.9805	ZHG	0.6995	0.0000	0.0000	0.981	0.984
AIC	4.1450	C(3)	1.5330	0.0000	0.0000	0.878	0.882
SBC	4.2765	C(4)	0.3915	0.0006	0.0017	0.947	0.969
J-Bera	0.1339	C(5)	-0.1053	0.2223	0.0974	0.953	0.963
		C(6)	0.1026	0.1844	0.2475	0.973	0.985
		C(7)	0.3828	0.0000	0.0000	0.496	0.450
		C(8)	-0.8355	0.0000	0.0000	0.599	0.723

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E2GARCH(2,1)+tsq	sample ind					
Z20	M71	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7845	C	-0.1605	0.3177	0.2128	0.941	0.939
s.e.	1.9857	ZHG	0.6990	0.0000	0.0000	0.983	0.985
AIC	4.1551	ZHG^2	-0.0001	0.9696	0.9779	0.868	0.871
SBC	4.3030	C(4)	1.5285	0.0000	0.0000	0.943	0.967
J-Bera	0.1439	C(5)	0.3936	0.0012	0.0014	0.950	0.962
		C(6)	-0.1098	0.2049	0.0902	0.971	0.984
		C(7)	0.1013	0.1971	0.2554	0.504	0.460
		C(8)	0.3796	0.0000	0.0000	0.607	0.736
		C(9)	-0.8306	0.0000	0.0000		

Fund: SWE*	E2GARCH(2,1)+tdm	sample ind					
Z20	M72	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7844	C	-0.1377	0.5158	0.3690	0.973	0.972
s.e.	1.9863	ZHG	0.7036	0.0000	0.0000	0.985	0.984
AIC	4.1547	ZHG*ZHG_TM	-0.0191	0.7909	0.8102	0.848	0.849
SBC	4.3026	C(4)	1.5144	0.0000	0.0000	0.934	0.960
J-Bera	0.1375	C(5)	0.4027	0.0009	0.0012	0.940	0.954
		C(6)	-0.1227	0.1513	0.0630	0.968	0.982
		C(7)	0.1012	0.2041	0.2494	0.523	0.484
		C(8)	0.3801	0.0000	0.0000	0.624	0.761
		C(9)	-0.8251	0.0000	0.0000		

Fund: SWE*	E2GARCH(1,2)	sample ind					
Z20	M73	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7865	C	-0.1607	0.2639	0.2167	0.429	0.428
s.e.	1.9716	ZHG	0.7358	0.0000	0.0000	0.730	0.718
AIC	4.1764	C(3)	0.7272	0.2784	0.3265	0.228	0.230
SBC	4.3078	C(4)	0.2161	0.0686	0.3029	0.362	0.393
J-Bera	0.0373	C(5)	-0.1578	0.3550	0.5190	0.378	0.409
		C(6)	-0.1673	0.0809	0.1380	0.203	0.313
		C(7)	-0.0570	0.7033	0.7294	0.270	0.399
		C(8)	0.3894	0.4720	0.5740	0.317	0.483

Fund: SWE*	E2GARCH(1,2)+tsq	sample ind					
Z20	M74	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7868	C	-0.0735	0.6761	0.6111	0.461	0.460
s.e.	1.9750	ZHG	0.7304	0.0000	0.0000	0.758	0.745
AIC	4.1813	ZHG^2	-0.0031	0.2110	0.4204	0.243	0.241
SBC	4.3292	C(4)	0.6951	0.1886	0.3198	0.365	0.410
J-Bera	0.0390	C(5)	0.1971	0.0853	0.3530	0.360	0.392
		C(6)	-0.1721	0.2528	0.4745	0.287	0.386
		C(7)	-0.1775	0.0609	0.1208	0.379	0.491
		C(8)	-0.0501	0.7127	0.7641	0.420	0.567
		C(9)	0.4309	0.2977	0.5043		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E2GARCH(1,2)+tdm	sample ind					
Z20	M75	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7879	C	0.0771	0.7414	0.6592	0.504	0.502
s.e.	1.9700	ZHG	0.7941	0.0000	0.0000	0.796	0.787
AIC	4.1733	ZHG*ZHG_T M	-0.1240	0.0913	0.1470	0.275	0.274
SBC	4.3212	C(4)	0.6842	0.1693	0.2869	0.400	0.452
J-Bera	0.0480	C(5)	0.2134	0.0634	0.3107	0.420	0.461
		C(6)	-0.1839	0.2213	0.4480	0.387	0.485
		C(7)	-0.1787	0.0623	0.1144	0.491	0.594
		C(8)	-0.0545	0.6796	0.7410	0.535	0.665
		C(9)	0.4336	0.2694	0.4747		

Fund: SWE*	E2GARCH(2,2)	sample ind					
Z20	M76	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7861	C	-0.0978	0.2761	0.3203	0.070	0.070
s.e.	1.9784	ZHG	0.7112	0.0000	0.0000	0.141	0.195
AIC	4.0132	C(3)	0.5574	0.0000	0.0000	0.206	0.322
SBC	4.1611	C(4)	-0.2352	0.0059	0.0489	0.297	0.360
J-Bera	0.8481	C(5)	0.2120	0.0222	0.0902	0.061	0.084
		C(6)	-0.1494	0.0039	0.0001	0.036	0.089
		C(7)	0.1219	0.0080	0.0108	0.042	0.052
		C(8)	1.4677	0.0000	0.0000	0.054	0.085
		C(9)	-0.9529	0.0000	0.0000		

Fund: SWE*	E2GARCH(2,2)+tsq	sample ind					
Z20	M77	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7853	C	-0.0922	0.5027	0.4445	0.065	0.063
s.e.	1.9872	ZHG	0.7061	0.0000	0.0000	0.159	0.250
AIC	4.0129	ZHG^2	-0.0040	0.0906	0.0993	0.199	0.371
SBC	4.1772	C(4)	0.5104	0.0000	0.0000	0.324	0.517
J-Bera	0.7347	C(5)	-0.2154	0.0020	0.0186	0.164	0.250
		C(6)	0.2419	0.0007	0.0377	0.169	0.303
		C(7)	-0.1186	0.0449	0.1023	0.174	0.201
		C(8)	0.1097	0.0498	0.1318	0.216	0.287
		C(9)	1.4583	0.0000	0.0000		
		C(10)	-0.9567	0.0000	0.0000		

Fund: SWE*	E2GARCH(2,2)+tdm	sample ind					
Z20	M78	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7869	C	0.0508	0.7387	0.7061	0.131	0.130
s.e.	1.9798	ZHG	0.7559	0.0000	0.0000	0.243	0.348
AIC	4.0283	ZHG*ZHG_T M	-0.1075	0.0419	0.0630	0.288	0.466
SBC	4.1926	C(4)	0.5472	0.0000	0.0000	0.439	0.616
J-Bera	0.6769	C(5)	-0.1999	0.0032	0.0427	0.250	0.331
		C(6)	0.1934	0.0035	0.0923	0.253	0.388
		C(7)	-0.1496	0.0065	0.0004	0.220	0.202
		C(8)	0.1287	0.0071	0.0091	0.289	0.283
		C(9)	1.4669	0.0000	0.0000		
		C(10)	-0.9602	0.0000	0.0000		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P1ARCH(1)	sample ind					
Z20	M79	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1397	0.2892	0.0000	0.509	0.513
s.e.	1.9605	ZHG	0.7364	0.0000		0.766	0.763
AIC	4.1438	C(3)	691.9782	0.9627	0.9732	0.188	0.210
SBC	4.2424	C(4)	0.0002	0.9732	0.8182	0.308	0.346
J-Bera	0.1335	C(5)	0.4222	0.8182	0.7589	0.392	0.450
		C(6)	11.0180	0.7589		0.315	0.459
						0.385	0.544
						0.432	0.614

Fund: SWE*	P1ARCH(1)+tsq	sample ind					
Z20	M80	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0611	0.7047	0.0000	0.601	0.604
s.e.	1.9643	ZHG	0.7299	0.0000	0.2388	0.831	0.830
AIC	4.1487	ZHG^2	-0.0031	0.2388		0.195	0.216
SBC	4.2637	C(4)	691.3784	0.9629	0.9746	0.307	0.350
J-Bera	0.1325	C(5)	0.0002	0.9746	0.8411	0.385	0.448
		C(6)	0.4566	0.8411	0.7600	0.378	0.514
		C(7)	11.0890	0.7600		0.461	0.610
						0.491	0.677

Fund: SWE*	P1ARCH(1)+tdm	sample ind					
Z20	M81	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7882	C	0.0795	0.7250	0.0000	0.597	0.600
s.e.	1.9587	ZHG	0.7887	0.0000	0.1331	0.824	0.823
AIC	4.1430	ZHG*ZHG_TM	-0.1160	0.1331		0.200	0.222
SBC	4.2580	C(4)	580.6666	0.9621	0.9795	0.314	0.359
J-Bera	0.1367	C(5)	0.0002	0.9795	0.9023	0.409	0.473
		C(6)	0.4946	0.9023	0.7613	0.436	0.562
		C(7)	10.8458	0.7613		0.516	0.652
						0.550	0.716

Fund: SWE*	P1ARCH(1,1)	sample ind					
Z20	M82	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1394	0.2901	0.0000	0.510	0.514
s.e.	1.9655	ZHG	0.7350	0.0000		0.689	0.681
AIC	4.1528	C(3)	362.8262	0.9420	0.9999	0.164	0.189
SBC	4.2678	C(4)	0.0001	0.9999	0.9997	0.275	0.318
J-Bera	0.1080	C(5)	0.6655	0.9997	0.9445	0.357	0.427
		C(6)	0.0064	0.9445	0.6645	0.288	0.437
		C(7)	10.0195	0.6645		0.357	0.522
						0.403	0.593

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P1ARCH(1,1)+tsq	sample ind					
Z20	M83	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0640	0.6917	0.0000	0.629	0.632
s.e.	1.9693	ZHG	0.7291	0.0000	0.2459	0.770	0.765
AIC	4.1583	ZHG^2	-0.0030	0.2459		0.172	0.194
SBC	4.2898	C(4)	198.3623	0.9316	1.0000	0.277	0.323
J-Bera	0.1084	C(5)	0.0001	1.0000	1.0000	0.358	0.429
		C(6)	0.9635	1.0000	0.9486	0.355	0.496
		C(7)	0.0060	0.9486	0.6459	0.435	0.589
		C(8)	9.0643	0.6459		0.458	0.656

Fund: SWE*	P1ARCH(1,1)+tdm	sample ind					
Z20	M84	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7882	C	0.0767	0.7341	0.0000	0.620	0.623
s.e.	1.9638	ZHG	0.7877	0.0000	0.1343	0.762	0.758
AIC	4.1524	ZHG*ZHG_T M	-0.1154	0.1343		0.179	0.203
SBC	4.2838	C(4)	213.8767	0.9388	1.0000	0.287	0.334
J-Bera	0.1117	C(5)	0.0001	1.0000	1.0000	0.381	0.453
		C(6)	0.9746	1.0000	0.9545	0.415	0.545
		C(7)	0.0044	0.9545	0.6774	0.493	0.631
		C(8)	9.2319	0.6774		0.521	0.697

Fund: SWE*	P1ARCH(2,1)	sample ind					
Z20	M85	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7857	C	-0.1454	0.2309	0.1925	0.762	0.757
s.e.	1.9750	ZHG	0.7110	0.0000	0.0000	0.933	0.960
AIC	4.1252	C(3)	3.6273	0.0063	0.0001	0.905	0.913
SBC	4.2567	C(4)	0.1888	0.0440	0.0044	0.967	0.984
J-Bera	0.4424	C(5)	0.5490	0.0888	0.0197	0.989	0.996
		C(6)	0.1059	0.4569	0.2752	0.916	0.939
		C(7)	-0.5968	0.0001	0.0000	0.704	0.701
		C(8)	1.5150	0.0015	0.0000	0.758	0.893

Fund: SWE*	P1ARCH(2,1)+tsq	sample ind					
Z20	M86	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0363	0.8262	0.7903	0.977	0.977
s.e.	1.9743	ZHG	0.7215	0.0000	0.0000	0.847	0.845
AIC	4.1517	ZHG^2	-0.0033	0.2082	0.2997	0.260	0.254
SBC	4.2996	C(4)	3.7717	0.1742	0.0136	0.401	0.432
J-Bera	0.2177	C(5)	0.0847	0.9804	0.9660	0.497	0.564
		C(6)	0.9656	0.9768	0.9593	0.431	0.553
		C(7)	0.2243	0.4070	0.1242	0.523	0.625
		C(8)	-0.2056	0.3017	0.2983	0.551	0.757
		C(9)	2.4152	0.0575	0.0101		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P1ARCH(2,1)+tdm	sample ind					
Z20	M87	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7879	C	0.0660	0.7589	0.6917	0.944	0.943
s.e.	1.9702	ZHG	0.7891	0.0000	0.0000	0.842	0.845
AIC	4.1515	ZHG*ZHG_T M	-0.1217	0.0915	0.1148	0.229	0.233
SBC	4.2994	C(4)	4.0076	0.1714	0.1234	0.354	0.394
J-Bera	0.1881	C(5)	0.0663	0.9865	0.9811	0.469	0.541
		C(6)	0.9559	0.9823	0.9751	0.446	0.578
		C(7)	0.1471	0.5785	0.4229	0.520	0.642
		C(8)	-0.1444	0.3761	0.5139	0.544	0.769
		C(9)	2.6770	0.0354	0.0763		

Fund: SWE*	P1ARCH(1,2)	sample ind					
Z20	M88	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1348	0.3976	0.2516	0.213	0.213
s.e.	1.9704	ZHG	0.7361	0.0000	0.0000	0.458	0.441
AIC	4.1659	C(3)	2.7242	0.2462	0.3226	0.429	0.417
SBC	4.2974	C(4)	0.0891	0.3004	0.4164	0.591	0.606
J-Bera	0.1460	C(5)	0.2350	0.6730	0.4915	0.528	0.543
		C(6)	-0.0758	0.3808	0.2488	0.285	0.384
		C(7)	0.4060	0.2938	0.4722	0.299	0.444
		C(8)	2.2311	0.0766	0.0006	0.357	0.518

Fund: SWE*	P1ARCH(1,2)+tsq	sample ind					
Z20	M89	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7870	C	-0.0508	0.7953	0.7030	0.287	0.286
s.e.	1.9742	ZHG	0.7276	0.0000	0.0000	0.564	0.539
AIC	4.1737	ZHG^2	-0.0031	0.2938	0.3777	0.461	0.444
SBC	4.3216	C(4)	2.7599	0.2956	0.3089	0.584	0.623
J-Bera	0.1045	C(5)	0.0912	0.2523	0.4299	0.520	0.540
		C(6)	0.1923	0.6951	0.5681	0.367	0.455
		C(7)	-0.0777	0.3678	0.2647	0.386	0.519
		C(8)	0.3945	0.3098	0.4669	0.444	0.614
		C(9)	2.2345	0.0859	0.0016		

Fund: SWE*	P1ARCH(1,2)+tdm	sample ind					
Z20	M90	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7872	C	0.0557	0.8007	0.7308	0.754	0.754
s.e.	1.9734	ZHG	0.7919	0.0000	0.0000	0.952	0.948
AIC	4.1434	ZHG*ZHG_T M	-0.1356	0.0673	0.0852	0.552	0.560
SBC	4.2913	C(4)	2.0691	0.0760	0.2043	0.696	0.742
J-Bera	0.1464	C(5)	0.1322	0.2673	0.2245	0.752	0.797
		C(6)	0.5715	0.3404	0.1862	0.708	0.787
		C(7)	-0.0700	0.2959	0.2800	0.774	0.845
		C(8)	0.3647	0.1404	0.3103	0.767	0.878
		C(9)	2.0923	0.0203	0.0005		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P1ARCH(2,2)	sample ind					
Z20	M91	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7871	C	-0.0752	0.6429	0.5293	0.188	0.188
s.e.	1.9741	ZHG	0.7367	0.0000	0.0000	0.406	0.396
AIC	4.1794	C(3)	3.0795	0.3796	0.5426	0.451	0.435
SBC	4.3273	C(4)	0.0787	0.3589	0.4642	0.615	0.621
J-Bera	0.1717	C(5)	0.2440	0.7059	0.5431	0.554	0.555
		C(6)	-0.0723	0.4463	0.4111	0.322	0.409
		C(7)	0.3876	0.4417	0.4701	0.338	0.476
		C(8)	-0.0544	0.8918	0.9269	0.398	0.546
		C(9)	2.2070	0.1317	0.0026		

Fund: SWE*	P1ARCH(2,2)+tsq	sample ind					
Z20	M92	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7863	C	-0.0862	0.6157	0.5115	0.725	0.724
s.e.	1.9829	ZHG	0.7187	0.0000	0.0000	0.939	0.940
AIC	4.1572	ZHG^2	-0.0036	0.1708	0.2820	0.554	0.559
SBC	4.3216	C(4)	2.3358	0.1168	0.1418	0.711	0.755
J-Bera	0.2302	C(5)	0.1142	0.3380	0.2759	0.726	0.769
		C(6)	0.5957	0.4292	0.2323	0.618	0.709
		C(7)	-0.0618	0.4188	0.3482	0.684	0.766
		C(8)	0.4103	0.1011	0.2272	0.684	0.835
		C(9)	-0.1362	0.5044	0.5675		
		C(10)	2.0135	0.0564	0.0024		

Fund: SWE*	P1ARCH(2,2)+tdm	sample ind					
Z20	M93	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7880	C	0.0630	0.7852	0.6938	0.609	0.608
s.e.	1.9747	ZHG	0.7877	0.0000	0.0000	0.876	0.867
AIC	4.1559	ZHG*ZHG_TM	-0.1150	0.1342	0.1295	0.709	0.706
SBC	4.3202	C(4)	2.6931	0.2769	0.3091	0.836	0.865
J-Bera	0.2389	C(5)	0.1158	0.2136	0.2584	0.834	0.861
		C(6)	0.3419	0.4701	0.2373	0.764	0.817
		C(7)	-0.0645	0.4446	0.4348	0.786	0.844
		C(8)	0.3876	0.1652	0.3786	0.809	0.910
		C(9)	-0.1152	0.6064	0.6369		
		C(10)	2.1900	0.1173	0.0102		

Fund: SWE*	P2ARCH(1,2)	sample ind					
Z20	M94	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7868	C	-0.1276	0.4243	0.2662	0.181	0.182
s.e.	1.9753	ZHG	0.7337	0.0000	0.0000	0.406	0.391
AIC	4.1742	C(3)	2.6994	0.4727	0.3155	0.459	0.445
SBC	4.3221	C(4)	0.0871	0.3768	0.4381	0.624	0.630
J-Bera	0.1419	C(5)	0.2143	0.7009	0.6142	0.554	0.565
		C(6)	-0.0722	0.4732	0.3550	0.289	0.385
		C(7)	-0.0325	0.6920	0.9457	0.301	0.447
		C(8)	0.4071	0.2937	0.4797	0.356	0.503
		C(9)	2.2356	0.2589	0.0004		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P2ARCH(1,2)+tsq	sample ind					
Z20	M95	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7875	C	-0.0227	0.9202	0.8639	0.138	0.137
s.e.	1.9773	ZHG	0.7305	0.0000	0.0000	0.329	0.308
AIC	4.2114	ZHG^2	-0.0020	0.5594	0.5542	0.331	0.311
SBC	4.3758	C(4)	3.1032	0.4167	0.3036	0.457	0.479
J-Bera	0.0693	C(5)	0.0726	0.4710	0.5406	0.373	0.376
		C(6)	0.1728	0.8035	0.7498	0.201	0.280
		C(7)	-0.0795	0.4432	0.3081	0.218	0.350
		C(8)	-0.0112	0.9798	0.9785	0.271	0.426
		C(9)	0.4247	0.4620	0.3881		
		C(10)	2.2419	0.2452	0.0031		

Fund: SWE*	P2ARCH(1,2)+tdm	sample ind					
Z20	M96	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7877	C	0.0661	0.7511	0.6843	0.660	0.660
s.e.	1.9760	ZHG	0.7971	0.0000	0.0000	0.905	0.893
AIC	4.1566	ZHG*ZHG_TM	-0.1245	0.0816	0.1218	0.571	0.572
SBC	4.3210	C(4)	2.2441	0.2662	0.3501	0.712	0.755
J-Bera	0.1862	C(5)	0.1199	0.2308	0.2516	0.732	0.776
		C(6)	0.3922	0.3937	0.2317	0.694	0.771
		C(7)	-0.0658	0.4784	0.5422	0.749	0.825
		C(8)	-0.0002	0.9997	0.9997	0.769	0.884
		C(9)	0.3648	0.3693	0.5316		
		C(10)	2.2109	0.1214	0.0021		

Fund: SWE*	P2ARCH(2,2)	sample ind					
Z20	M97	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7868	C	-0.1166	0.4012	0.3106	0.553	0.553
s.e.	1.9803	ZHG	0.7290	0.0000	0.0000	0.837	0.828
AIC	4.1659	C(3)	2.7984	0.3119	0.3584	0.702	0.700
SBC	4.3303	C(4)	0.1164	0.2463	0.2308	0.838	0.852
J-Bera	0.2344	C(5)	0.3309	0.4929	0.3298	0.844	0.859
		C(6)	-0.0586	0.5709	0.6294	0.601	0.675
		C(7)	-0.0332	0.9634	0.9649	0.628	0.706
		C(8)	0.3633	0.4059	0.5665	0.662	0.767
		C(9)	-0.1240	0.5872	0.6912		
		C(10)	2.1811	0.1519	0.0034		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P2ARCH(2,2)+tsq	sample ind					
Z20	M98	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7875	C	-0.0206	0.9238	0.8785	0.185	0.183
s.e.	1.9824	ZHG	0.7307	0.0000	0.0000	0.415	0.386
AIC	4.2067	ZHG^2	-0.0020	0.5356	0.5577	0.354	0.336
SBC	4.3875	C(4)	3.2013	0.4740	0.5861	0.478	0.509
J-Bera	0.0919	C(5)	0.0765	0.4072	0.5161	0.417	0.433
		C(6)	0.1724	0.7819	0.7438	0.249	0.339
		C(7)	-0.0700	0.5068	0.4857	0.262	0.402
		C(8)	-0.0255	0.9559	0.9567	0.319	0.505
		C(9)	0.3848	0.5790	0.5000		
		C(10)	-0.0583	0.9009	0.9163		
		C(11)	2.2079	0.2616	0.0459		

Fund: SWE*	P2ARCH(2,2)+tdm	sample ind					
Z20	M99	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7882	C	0.1235	0.6142	0.4443	0.454	0.452
s.e.	1.9792	ZHG	0.7856	0.0000	0.0000	0.755	0.737
AIC	4.1708	ZHG*ZHG_TM	-0.1280	0.1118	0.1010	0.604	0.598
SBC	4.3515	C(4)	2.7558	0.3105	0.4283	0.729	0.770
J-Bera	0.1518	C(5)	0.1070	0.2370	0.3158	0.741	0.779
		C(6)	0.2620	0.5743	0.4711	0.651	0.730
		C(7)	-0.0624	0.5380	0.5819	0.663	0.761
		C(8)	-0.0611	0.9204	0.9248	0.698	0.846
		C(9)	0.3783	0.3501	0.5338		
		C(10)	-0.0918	0.7181	0.7621		
		C(11)	2.1964	0.1548	0.0158		

Fund: SWE*	ARCH-M(1)	sample ind					
Z20	M100	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7947	@SQRT(GARCH)	1.7380	0.2537	0.2127	0.651	0.654
s.e.	1.9184	C	-3.2947	0.2464	0.2080	0.731	0.728
AIC	4.1461	ZHG	0.7222	0.0000	0.0000	0.241	0.268
SBC	4.2283	C	3.1551	0.0000	0.0000	0.342	0.391
J-Bera	0.0531	RESID(-1)^2	0.1210	0.0982	0.2650	0.398	0.475
						0.364	0.511
						0.409	0.572
						0.456	0.666

Fund: SWE*	ARCH-M(1)+tsq	sample ind					
Z20	M101	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7951	@SQRT(GARCH)	1.6970	0.2485	0.1977	0.714	0.716
s.e.	1.9215	C	-3.1644	0.2508	0.1969	0.769	0.766
AIC	4.1539	ZHG	0.7172	0.0000	0.0000	0.234	0.259
SBC	4.2525	ZHG^2	-0.0020	0.4531	0.5930	0.313	0.358
J-Bera	0.0430	C	3.1356	0.0000	0.0000	0.367	0.441
		RESID(-1)^2	0.1266	0.0883	0.2491	0.380	0.514
						0.428	0.581
						0.467	0.679

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	ARCH-M(1)+tdm	sample ind					
Z20	M102	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7959	@SQRT(GARCH)	1.5764	0.2371	0.1826	0.759	0.761
s.e.	1.9178	C	-2.7996	0.2657	0.1994	0.786	0.783
AIC	4.1486	ZHG	0.7657	0.0000	0.0000	0.240	0.263
SBC	4.2473	ZHG*ZHG_TM	-0.0962	0.1970	0.2744	0.311	0.355
J-Bera	0.0323	C	3.0922	0.0000	0.0000	0.386	0.457
		RESID(-1)^2	0.1366	0.0701	0.2257	0.439	0.554
						0.480	0.617
						0.525	0.722

Fund: SWE*	GARCH-M(1,1)	sample ind					
Z20	M103	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7910	@SQRT(GARCH)	1.0767	0.0000	0.0458	0.739	0.742
s.e.	1.9404	C	-2.1239	0.0000	0.0256	0.934	0.926
AIC	4.1174	ZHG	0.7135	0.0000	0.0000	0.891	0.898
SBC	4.2160	C	0.0389	0.0018	0.2940	0.901	0.900
J-Bera	0.0000	RESID(-1)^2	-0.0311	0.0000	0.0285	0.831	0.844
		GARCH(-1)	1.0137	0.0000	0.0000	0.718	0.732
						0.681	0.680
						0.770	0.778

Fund: SWE*	GARCH-M(1,1)+tsq	sample ind					
Z20	M104	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8001	@SQRT(GARCH)	-16.9596	0.7602	0.6709	0.129	0.126
s.e.	1.9027	C	31.6088	0.7589	0.6736	0.312	0.216
AIC	4.1607	ZHG	0.7292	0.0000	0.0000	0.466	0.395
SBC	4.2757	ZHG^2	-0.0037	0.1777	0.3390	0.591	0.540
J-Bera	0.0001	C	3.6930	0.0009	0.0001	0.670	0.646
		RESID(-1)^2	-0.0097	0.7742	0.6446	0.422	0.349
		GARCH(-1)	-0.0564	0.8197	0.8144	0.136	0.031
						0.193	0.085

Fund: SWE*	GARCH-M(1,1)+tdm	sample ind					
Z20	M105	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8013	@SQRT(GARCH)	21.9888	0.7874	0.2497	0.000	0.000
s.e.	1.8970	C	-40.6689	0.7887	0.2645	0.000	0.000
AIC	4.1514	ZHG	0.7870	0.0000	0.0000	0.000	0.000
SBC	4.2664	ZHG*ZHG_TM	-0.1186	0.1455	0.1731	0.000	0.000
J-Bera	0.0000	C	3.0603	0.0600	0.0002	0.000	0.000
		RESID(-1)^2	0.0079	0.7777	0.3188	0.000	0.000
		GARCH(-1)	0.1054	0.8109	0.5947	0.000	0.000
						0.000	0.000

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	GARCH-M(2,1)	sample ind					
Z20	M106	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7926	@SQRT(GARCH)	1.4707	0.0159	0.0376	0.843	0.845
s.e.	1.9379	C	-2.8505	0.0074	0.0268	0.697	0.702
AIC	4.1467	ZHG	0.7236	0.0000	0.0000	0.788	0.784
SBC	4.2617	C	0.0774	0.0418	0.7121	0.898	0.899
J-Bera	0.4053	RESID(-1)^2	-0.0223	0.0255	0.6968	0.929	0.929
		GARCH(-1)	0.5714	0.0000	0.8803	0.871	0.876
		GARCH(-2)	0.4194	0.0000	0.9113	0.897	0.898
						0.942	0.945

Fund: SWE*	GARCH-M(2,1)+tsq	sample ind					
Z20	M107	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7889	@SQRT(GARCH)	0.8207	0.0658	0.0656	0.320	0.325
s.e.	1.9605	C	-1.5913	0.0461	0.0466	0.591	0.575
AIC	4.1327	ZHG	0.7034	0.0000	0.0000	0.520	0.516
SBC	4.2642	ZHG^2	-0.0023	0.2885	0.4074	0.536	0.571
J-Bera	0.0000	C	0.0841	0.0000	0.4686	0.387	0.394
		RESID(-1)^2	-0.0560	0.0000	0.3193	0.234	0.328
		GARCH(-1)	0.6684	0.0000	0.6868	0.223	0.352
		GARCH(-2)	0.3538	0.0000	0.8326	0.279	0.433

Fund: SWE*	GARCH-M(2,1)+tdm	sample ind					
Z20	M108	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8020	@SQRT(GARCH)	26.5742	0.7277	0.6420	0.000	0.000
s.e.	1.8985	C	-48.7979	0.7291	0.6445	0.000	0.000
AIC	4.1580	ZHG	0.7838	0.0000	0.0000	0.000	0.000
SBC	4.2895	ZHG*ZHG_TM	-0.1168	0.1443	0.1773	0.000	0.000
J-Bera	0.0000	C	3.1906	0.0434	0.0090	0.000	0.000
		RESID(-1)^2	0.0069	0.7211	0.6631	0.000	0.000
		GARCH(-1)	0.0332	0.9452	0.8832	0.000	0.000
		GARCH(-2)	0.0203	0.9413	0.8413	0.000	0.000

Fund: SWE*	GARCH-M(1,2)	sample ind					
Z20	M109	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8022	@SQRT(GARCH)	1.8107	0.0000	0.0172	0.415	0.419
s.e.	1.8927	C	-3.2504	0.0000	0.0139	0.704	0.702
AIC	4.0974	ZHG	0.6954	0.0000	0.0000	0.747	0.763
SBC	4.2124	C	0.0109	0.0344	0.6969	0.803	0.793
J-Bera	0.1560	RESID(-1)^2	0.1256	0.0000	0.0254	0.897	0.900
		RESID(-2)^2	-0.1443	0.0000	0.0153	0.861	0.860
		GARCH(-1)	1.0105	0.0000	0.0000	0.851	0.796
						0.909	0.892

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	GARCH-M(1,2)+tsq	sample ind					
Z20	M110	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7974	@SQRT(GARCH)	2.0242	0.1441	0.1279	0.686	0.688
s.e.	1.9205	C	-3.6882	0.1493	0.1297	0.916	0.926
AIC	4.1525	ZHG	0.7221	0.0000	0.0000	0.572	0.591
SBC	4.2840	ZHG^2	-0.0031	0.2325	0.3916	0.655	0.677
J-Bera	0.0595	C	1.8902	0.1149	0.1914	0.687	0.700
		RESID(-1)^2	0.1083	0.0775	0.2127	0.690	0.749
		RESID(-2)^2	-0.0830	0.2054	0.2057	0.779	0.839
		GARCH(-1)	0.4303	0.2466	0.3489	0.797	0.863

Fund: SWE*	GARCH-M(1,2)+tdm	sample ind					
Z20	M111	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7979	@SQRT(GARCH)	1.7999	0.1282	0.1158	0.724	0.727
s.e.	1.9180	C	-3.1317	0.1533	0.1318	0.937	0.944
AIC	4.1474	ZHG	0.7806	0.0000	0.0000	0.584	0.601
SBC	4.2789	ZHG*ZHG_TM	-0.1136	0.1268	0.1774	0.664	0.685
J-Bera	0.0504	C	1.8930	0.1094	0.2279	0.734	0.745
		RESID(-1)^2	0.1190	0.0572	0.1909	0.760	0.804
		RESID(-2)^2	-0.0888	0.1776	0.2131	0.835	0.880
		GARCH(-1)	0.4232	0.2527	0.4051	0.856	0.901

Fund: SWE*	GARCH-M(2,2)	sample ind					
Z20	M112	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7964	@SQRT(GARCH)	2.0055	0.1813	0.1407	0.620	0.623
s.e.	1.9250	C	-3.7407	0.1775	0.1347	0.884	0.891
AIC	4.1567	ZHG	0.7271	0.0000	0.0000	0.674	0.689
SBC	4.2881	C	2.0453	0.2224	0.3074	0.807	0.817
J-Bera	0.0853	RESID(-1)^2	0.1057	0.0988	0.2299	0.835	0.843
		RESID(-2)^2	-0.0787	0.2771	0.2621	0.709	0.776
		GARCH(-1)	0.4824	0.2088	0.4347	0.793	0.857
		GARCH(-2)	-0.0957	0.6932	0.7198	0.817	0.866

Fund: SWE*	GARCH-M(2,2)+tsq	sample ind					
Z20	M113	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7989	@SQRT(GARCH)	1.7293	0.0001	0.0108	0.409	0.413
s.e.	1.9184	C	-3.1805	0.0001	0.0072	0.696	0.696
AIC	4.1154	ZHG	0.6981	0.0000	0.0000	0.765	0.781
SBC	4.2633	ZHG^2	-0.0010	0.7010	0.6786	0.838	0.832
J-Bera	0.2234	C	0.0400	0.4193	0.4208	0.918	0.923
		RESID(-1)^2	0.1106	0.0000	0.0407	0.875	0.873
		RESID(-2)^2	-0.1435	0.0000	0.0104	0.884	0.834
		GARCH(-1)	0.7505	0.0000	0.0102	0.928	0.912
		GARCH(-2)	0.2636	0.0000	0.3725		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	GARCH-M(2,2)+tdm	sample ind					
Z20	M114	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7962	@SQRT(GARCH)	1.4016	0.0022	0.0138	0.340	0.344
s.e.	1.9314	C	-2.4479	0.0054	0.0147	0.595	0.594
AIC	4.1080	ZHG	0.7459	0.0000	0.0000	0.630	0.657
SBC	4.2559	ZHG*ZHG_TM	-0.1083	0.1639	0.1127	0.702	0.698
J-Bera	0.2061	C	0.0639	0.1740	0.1929	0.819	0.831
		RESID(-1)^2	0.0809	0.2389	0.1182	0.826	0.836
		RESID(-2)^2	-0.1251	0.0549	0.0171	0.865	0.850
		GARCH(-1)	0.7167	0.0000	0.0593	0.913	0.917
		GARCH(-2)	0.3003	0.0000	0.4344		

Fund: SWE*	T1ARCH-M(1)	sample ind					
Z20	M115	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7966	@SQRT(GARCH)	1.8413	0.4422	0.0897	0.894	0.894
s.e.	1.9143	C	-3.5181	0.4259	0.0886	0.883	0.882
AIC	4.1442	ZHG	0.7213	0.0000	0.0000	0.216	0.230
SBC	4.2428	C	3.1673	0.0000	0.0000	0.322	0.365
J-Bera	0.0936	RESID(-1)^2	0.0452	0.5958	0.3091	0.426	0.492
		RESID(-1)^2*(RESID(-1)<0)	0.1236	0.3957	0.2901	0.372	0.508
						0.399	0.539
						0.422	0.651

Fund: SWE*	T1ARCH-M(1)+tsq	sample ind					
Z20	M116	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7970	@SQRT(GARCH)	1.8301	0.4248	0.0875	0.943	0.943
s.e.	1.9176	C	-3.4508	0.4145	0.0899	0.883	0.883
AIC	4.1525	ZHG	0.7169	0.0000	0.0000	0.215	0.227
SBC	4.2675	ZHG^2	-0.0017	0.5094	0.6450	0.302	0.340
J-Bera	0.0842	C	3.1513	0.0000	0.0000	0.402	0.467
		RESID(-1)^2	0.0496	0.5571	0.2881	0.399	0.523
		RESID(-1)^2*(RESID(-1)<0)	0.1241	0.3859	0.2965	0.426	0.561
						0.440	0.672

Fund: SWE*	T1ARCH-M(1)+tdm	sample ind					
Z20	M117	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7980	@SQRT(GARCH)	1.7853	0.4075	0.0817	0.969	0.969
s.e.	1.9126	C	-3.2258	0.4162	0.0972	0.874	0.874
AIC	4.1466	ZHG	0.7635	0.0000	0.0000	0.222	0.233
SBC	4.2617	ZHG*ZHG_TM	-0.0944	0.1953	0.2831	0.298	0.334
J-Bera	0.0704	C	3.1173	0.0000	0.0000	0.407	0.469
		RESID(-1)^2	0.0527	0.5203	0.2840	0.458	0.562
		RESID(-1)^2*(RESID(-1)<0)	0.1322	0.3652	0.2866	0.478	0.601
						0.495	0.716

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

T1ARCH-M(1,1)
M118

Errors generated – model rejected

T1ARCH-M(1,1)+tsq
M119

Errors generated – model rejected

Fund: SWE*	T1ARCH-M(1,1)+tdm	sample ind					
Z20	M120	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7976	@SQRT(GARCH)	2.1444	0.4842	0.1832	0.567	0.571
s.e.	1.9193	C	-3.8298	0.4952	0.2018	0.670	0.672
AIC	4.1517	ZHG	0.7814	0.0000	0.0000	0.205	0.235
SBC	4.2832	ZHG*ZHG_TM	-0.1221	0.1107	0.1506	0.272	0.313
J-Bera	0.0821	C	2.4087	0.0218	0.1053	0.340	0.402
		RESID(-1)^2	0.0103	0.8626	0.7521	0.379	0.499
		RESID(-1)^2*(RESID(-1)<0)	0.1261	0.3820	0.3829	0.481	0.616
		GARCH(-1)	0.2299	0.4032	0.6208	0.518	0.691

T1ARCH-M(2,1)
M121 |

Errors generated – model rejected

Fund: SWE*	T1ARCH-M(2,1)+tsq	sample ind					
Z20	M122	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7917	@SQRT(GARCH)	0.9944	0.2748	0.1368	0.140	0.144
s.e.	1.9522	C	-1.8202	0.2599	0.1345	0.285	0.273
AIC	4.1299	ZHG	0.7235	0.0000	0.0000	0.187	0.200
SBC	4.2778	ZHG^2	-0.0047	0.0427	0.0000	0.266	0.330
J-Bera	0.1678	C	1.6214	0.0000	0.0001	0.299	0.381
		RESID(-1)^2	-0.0499	0.0315	0.0773	0.140	0.274
		RESID(-1)^2*(RESID(-1)<0)	0.1621	0.0237	0.1196	0.208	0.370
		GARCH(-1)	0.9646	0.0000	0.0000	0.228	0.485
		GARCH(-2)	-0.4692	0.0001	0.0003		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T1ARCH-M(2,1)+tdm	sample ind					
Z20	M123	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7935	@SQRT(GARCH)	1.0014	0.0758	0.0000	0.198	0.202
s.e.	1.9441	C	-1.6649	0.1103	0.0000	0.357	0.349
AIC	4.1246	ZHG	0.8025	0.0000	0.0000	0.226	0.227
SBC	4.2725	ZHG*ZHG_TM	-0.1402	0.0432	0.0802	0.318	0.371
J-Bera	0.2216	C	1.6340	0.0000	0.0002	0.380	0.459
		RESID(-1)^2	-0.0506	0.1291	0.0562	0.181	0.313
		RESID(-1)^2*(RESID(-1)<0)	0.1821	0.0059	0.0898	0.259	0.415
		GARCH(-1)	0.9275	0.0000	0.0002	0.293	0.609
		GARCH(-2)	-0.4513	0.0099	0.0016		

Fund: SWE*	T1ARCH-M(1,2)	sample ind					
Z20	M124	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7956	@SQRT(GARCH)	1.0720	0.2515	0.0419	0.976	0.976
s.e.	1.9290	C	-2.0604	0.2212	0.0340	0.980	0.981
AIC	4.1459	ZHG	0.7315	0.0000	0.0000	0.481	0.498
SBC	4.2774	C	2.1633	0.0115	0.1238	0.647	0.675
J-Bera	0.1123	RESID(-1)^2	0.0451	0.6495	0.3814	0.752	0.770
		RESID(-1)^2*(RESID(-1)<0)	0.1796	0.2185	0.1907	0.553	0.644
		RESID(-2)^2	-0.0788	0.1825	0.0322	0.649	0.734
		GARCH(-1)	0.3273	0.2030	0.4722	0.669	0.755

T1ARCH-M(1,2)+tsq
M125

Errors generated – model rejected

T1ARCH-M(1,2)+tdm
M126

Errors generated – model rejected

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T1ARCH-M(2,2)	sample ind					
Z20	M127	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7954	@SQRT(GARCH)	1.0752	0.2818	0.0389	0.957	0.958
s.e.	1.9352	C	-2.0604	0.2547	0.0299	0.993	0.994
AIC	4.1537	ZHG	0.7284	0.0000	0.0000	0.566	0.581
SBC	4.3016	C	2.2819	0.0202	0.1297	0.729	0.754
J-Bera	0.1460	RESID(-1)^2	0.0388	0.6883	0.4502	0.820	0.845
		RESID(-1)^2*(RESID(-1)<0)	0.1753	0.2453	0.1906	0.534	0.632
		RESID(-2)^2	-0.0679	0.2616	0.1578	0.639	0.729
		GARCH(-1)	0.4062	0.0872	0.4607	0.659	0.784
		GARCH(-2)	-0.1176	0.6502	0.6608		

Fund: SWE*	T1ARCH-M(2,2)+tsq	sample ind					
Z20	M128	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8025	@SQRT(GARCH)	2.2892	0.0001	0.0042	0.917	0.917
s.e.	1.9062	C	-4.1094	0.0002	0.0025	0.951	0.953
AIC	4.1033	ZHG	0.7093	0.0000	0.0000	0.991	0.986
SBC	4.2676	ZHG^2	-0.0012	0.6574	0.2813	0.996	0.994
J-Bera	0.6755	C	0.0893	0.0239	0.1445	0.984	0.988
		RESID(-1)^2	0.0514	0.3654	0.1723	0.874	0.872
		RESID(-1)^2*(RESID(-1)<0)	0.0465	0.0017	0.3255	0.675	0.609
		RESID(-2)^2	-0.1084	0.0568	0.0155	0.760	0.712
		GARCH(-1)	0.5940	0.0285	0.0405		
		GARCH(-2)	0.4032	0.1280	0.1655		

Fund: SWE*	T1ARCH-M(2,2)+tdm	sample ind					
Z20	M129	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	-6722.0218	@SQRT(GARCH)	2.8484	0.0000	0.0000	0.000	0.000
s.e.	351.6743	C	-6.6530	0.0000	0.0000	0.000	0.000
AIC	5.4137	ZHG	0.6065	0.0000	0.0000	0.000	0.000
SBC	5.5781	ZHG*ZHG_TM	0.3321	0.0000		0.000	0.000
J-Bera	0.0000	C	-0.3471	0.0000	0.0000	0.000	0.000
		RESID(-1)^2	0.1256	0.0000	0.0000	0.000	0.000
		RESID(-1)^2*(RESID(-1)<0)	0.1408	0.0000	0.0000	0.000	0.000
		RESID(-2)^2	-0.1335	0.0000	0.0000	0.000	0.000
		GARCH(-1)	0.5406	0.0000	0.0000		
		GARCH(-2)	0.4679	0.0000			

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH-M(1)	sample ind					
Z20	M130	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7977	@SQRT(GARCH)	2.2673	0.4201	0.0909	0.883	0.884
s.e.	1.9143	C	-4.3066	0.4060	0.0912	0.948	0.947
AIC	4.1523	ZHG	0.7232	0.0000	0.0000	0.263	0.280
SBC	4.2674	C	3.2249	0.0000	0.0000	0.384	0.423
J-Bera	0.0897	RESID(-1)^2	0.0535	0.5014	0.2449	0.488	0.541
		RESID(-1)^2*(RESID(-1)<0)	0.0978	0.4178	0.3391	0.475	0.591
		RESID(-2)^2*(RESID(-2)<0)	-0.0305	0.5067	0.4020	0.503	0.628
						0.517	0.702

Fund: SWE*	T2ARCH-M(1)+tsq	sample ind					
Z20	M131	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7979	@SQRT(GARCH)	2.2486	0.4136	0.0904	0.920	0.921
s.e.	1.9179	C	-4.2279	0.4039	0.0944	0.945	0.944
AIC	4.1608	ZHG	0.7188	0.0000	0.0000	0.261	0.277
SBC	4.2922	ZHG^2	-0.0016	0.5320	0.6616	0.362	0.400
J-Bera	0.0780	C	3.2127	0.0000	0.0000	0.465	0.520
		RESID(-1)^2	0.0554	0.4898	0.2438	0.493	0.599
		RESID(-1)^2*(RESID(-1)<0)	0.1004	0.4096	0.3362	0.521	0.641
		RESID(-2)^2*(RESID(-2)<0)	-0.0300	0.5154	0.4263	0.523	0.715

Fund: SWE*	T2ARCH-M(1)+tdm	sample ind					
Z20	M132	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7989	@SQRT(GARCH)	2.1824	0.4010	0.0853	0.943	0.944
s.e.	1.9132	C	-3.9642	0.4059	0.1015	0.932	0.932
AIC	4.1550	ZHG	0.7638	0.0000	0.0000	0.271	0.287
SBC	4.2865	ZHG*ZHG_TM	-0.0917	0.2066	0.2959	0.358	0.395
J-Bera	0.0621	C	3.1829	0.0000	0.0000	0.475	0.530
		RESID(-1)^2	0.0568	0.4749	0.2433	0.549	0.636
		RESID(-1)^2*(RESID(-1)<0)	0.1094	0.3865	0.3206	0.568	0.676
		RESID(-2)^2*(RESID(-2)<0)	-0.0313	0.5146	0.4239	0.569	0.751

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH-M(1,1)	sample ind					
Z20	M133	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8086	@SQRT(GARCH)	2.2798	0.0000	0.0111	0.280	0.285
s.e.	1.8665	C	-4.2001	0.0000	0.0076	0.331	0.364
AIC	4.0737	ZHG	0.6946	0.0000	0.0000	0.515	0.570
SBC	4.2052	C	0.0605	0.0124	0.0036	0.676	0.794
J-Bera	0.3980	RESID(-1)^2	-0.0368	0.0000	0.0446	0.729	0.907
		RESID(-1)^2*(RESID(-1)<0)	0.2098	0.0000	0.0110	0.373	0.601
		RESID(-2)^2*(RESID(-2)<0)	-0.1878	0.0000	0.0221	0.315	0.569
		GARCH(-1)	1.0015	0.0000	0.0000	0.397	0.678

Fund: SWE*	T2ARCH-M(1,1)+tsq	sample ind					
Z20	M134	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8047	@SQRT(GARCH)	11.9935	0.5507	0.0745	0.000	0.000
s.e.	1.8907	C	-22.0473	0.5512	0.0793	0.000	0.000
AIC	4.1500	ZHG	0.7189	0.0000	0.0000	0.000	0.000
SBC	4.2979	ZHG^2	-0.0031	0.2310	0.4057	0.000	0.000
J-Bera	0.0000	C	2.3668	0.1474	0.0040	0.000	0.000
		RESID(-1)^2	0.0056	0.6542	0.5369	0.000	0.000
		RESID(-1)^2*(RESID(-1)<0)	0.0242	0.5510	0.3095	0.000	0.000
		RESID(-2)^2*(RESID(-2)<0)	-0.0160	0.6537	0.4130	0.000	0.000
		GARCH(-1)	0.2892	0.5435	0.1957		

Fund: SWE*	T2ARCH-M(1,1)+tdm	sample ind					
Z20	M135	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8063	@SQRT(GARCH)	2.0979	0.0000	0.0121	0.704	0.707
s.e.	1.8827	C	-3.7455	0.0000	0.0135	0.739	0.748
AIC	4.0800	ZHG	0.7221	0.0000	0.0000	0.890	0.879
SBC	4.2279	ZHG*ZHG_TM	-0.0495	0.4819	0.4756	0.956	0.960
J-Bera	0.4793	C	0.0718	0.0006	0.0042	0.974	0.989
		RESID(-1)^2	-0.0417	0.0000	0.1558	0.808	0.844
		RESID(-1)^2*(RESID(-1)<0)	0.2036	0.0000	0.0159	0.739	0.750
		RESID(-2)^2*(RESID(-2)<0)	-0.1788	0.0000	0.0262	0.818	0.835
		GARCH(-1)	1.0005	0.0000	0.0000		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH-M(2,1)	sample ind					
Z20	M136	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7949	@SQRT(GARCH)	2.2304	0.0001	0.0362	0.095	0.098
s.e.	1.9374	C	-4.1844	0.0001	0.0294	0.245	0.251
AIC	4.1296	ZHG	0.7149	0.0000	0.0000	0.414	0.428
SBC	4.2775	C	0.0661	0.0000	0.2963	0.498	0.479
J-Bera	0.5714	RESID(-1)^2	-0.0587	0.0000	0.2665	0.611	0.611
		RESID(-1)^2*(RESID(-1)<0)	0.0615	0.0003	0.4830	0.633	0.569
		RESID(-2)^2*(RESID(-2)<0)	-0.0153	0.2764	0.7668	0.501	0.298
		GARCH(-1)	0.3263	0.0000	0.4858	0.610	0.428
		GARCH(-2)	0.6800	0.0000	0.1359		

Fund: SWE*	T2ARCH-M(2,1)+tsq	sample ind					
Z20	M137	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7966	@SQRT(GARCH)	2.1380	0.0010	0.0866	0.063	0.065
s.e.	1.9342	C	-3.9976	0.0004	0.0810	0.176	0.160
AIC	4.1403	ZHG	0.7078	0.0000	0.0000	0.303	0.293
SBC	4.3046	ZHG^2	0.0001	0.2424	0.9757	0.335	0.292
J-Bera	0.3025	C	0.0580	0.3693	0.4392	0.461	0.427
		RESID(-1)^2	-0.0508	0.2788	0.3604	0.517	0.462
		RESID(-1)^2*(RESID(-1)<0)	0.0625	0.1170	0.5148	0.439	0.276
		RESID(-2)^2*(RESID(-2)<0)	-0.0211	0.5342	0.7174	0.545	0.429
		GARCH(-1)	0.3327	0.5284	0.5129		
		GARCH(-2)	0.6717	0.2057	0.1755		

Fund: SWE*	T2ARCH-M(2,1)+tdm	sample ind					
Z20	M138	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.5615	@SQRT(GARCH)	2.2875	0.0000	0.0000	0.000	0.000
s.e.	2.8400	C	-5.6858	0.0000	0.0000	0.000	0.000
AIC	6.9543	ZHG	0.7107	0.0000	0.0000	0.000	0.000
SBC	7.1187	ZHG*ZHG_TM	-0.1396	0.0000		0.000	0.000
J-Bera	0.0000	C	0.0444	0.0000	0.0000	0.000	0.000
		RESID(-1)^2	0.0190	0.0000	0.0000	0.000	0.000
		RESID(-1)^2*(RESID(-1)<0)	0.1440	0.0000	0.0000	0.000	0.000
		RESID(-2)^2*(RESID(-2)<0)	0.5160	0.0000	0.0000	0.000	0.000
		GARCH(-1)	0.6113	0.0000	0.0000		
		GARCH(-2)	0.1993	0.0000			

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	T2ARCH-M(1,2)	sample ind					
Z20	M139	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8001	@SQRT(GARCH)	2.1653	0.2251	0.0600	0.979	0.979
s.e.	1.9127	C	-4.0697	0.2081	0.0570	0.976	0.977
AIC	4.1492	ZHG	0.7327	0.0000	0.0000	0.440	0.453
SBC	4.2972	C	1.5396	0.1863	0.0764	0.608	0.615
J-Bera	0.1932	RESID(-1)^2	0.0481	0.4521	0.2576	0.700	0.693
		RESID(-1)^2*(RESID(-1)<0)	0.1174	0.2848	0.2434	0.641	0.708
		RESID(-2)^2	-0.0467	0.3973	0.2087	0.735	0.797
		RESID(-2)^2*(RESID(-2)<0)	-0.0926	0.4149	0.2145	0.733	0.780
		GARCH(-1)	0.5374	0.1349	0.0502		

Fund: SWE*	T2ARCH-M(1,2)+tsq	sample ind					
Z20	M140	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8001	@SQRT(GARCH)	1.9724	0.2052	0.0549	0.928	0.928
s.e.	1.9177	C	-3.6169	0.1955	0.0590	0.961	0.959
AIC	4.1532	ZHG	0.7254	0.0000	0.0000	0.477	0.492
SBC	4.3175	ZHG^2	-0.0033	0.1906	0.3561	0.632	0.637
J-Bera	0.1353	C	1.6818	0.1098	0.0682	0.734	0.722
		RESID(-1)^2	0.0457	0.5216	0.2608	0.748	0.779
		RESID(-1)^2*(RESID(-1)<0)	0.1384	0.2512	0.2021	0.834	0.863
		RESID(-2)^2	-0.0545	0.3484	0.1198	0.811	0.843
		RESID(-2)^2*(RESID(-2)<0)	-0.0858	0.4624	0.2434		
		GARCH(-1)	0.4906	0.1367	0.0983		

Fund: SWE*	T2ARCH-M(1,2)+tdm	sample ind					
Z20	M141	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8008	@SQRT(GARCH)	1.8215	0.2136	0.0484	0.912	0.913
s.e.	1.9141	C	-3.1897	0.2224	0.0645	0.964	0.962
AIC	4.1467	ZHG	0.7882	0.0000	0.0000	0.492	0.508
SBC	4.3110	ZHG*ZHG_TM	-0.1220	0.0969	0.1363	0.645	0.650
J-Bera	0.1192	C	1.7062	0.0995	0.0875	0.762	0.754
		RESID(-1)^2	0.0443	0.5604	0.2648	0.808	0.828
		RESID(-1)^2*(RESID(-1)<0)	0.1556	0.2391	0.1792	0.880	0.898
		RESID(-2)^2	-0.0556	0.3475	0.1019	0.864	0.885
		RESID(-2)^2*(RESID(-2)<0)	-0.0905	0.4673	0.2475		
		GARCH(-1)	0.4778	0.1448	0.1447		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

T2ARCH-M(2,2)
M142

Errors generated – model rejected

T2ARCH-M(2,2)+tsq
M143

Errors generated – model rejected

Fund: SWE*	T2ARCH-M(2,2)+tdm	sample ind					
Z20	M144	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8047	@SQRT(GARCH)	2.0603	0.0002	0.0015	0.945	0.946
s.e.	1.9004	C	-3.5960	0.0002	0.0016	0.959	0.960
AIC	4.0954	ZHG	0.7455	0.0000	0.0000	0.980	0.974
SBC	4.2762	ZHG*ZHG_TM	-0.0695	0.3376	0.3092	0.981	0.980
J-Bera	0.5200	C	0.0956	0.0003	0.0019	0.989	0.993
		RESID(-1)^2	0.0342	0.6698	0.4420	0.932	0.931
		RESID(-1)^2*(RESID(-1)<0)	0.1152	0.2954	0.1083	0.883	0.832
		RESID(-2)^2	-0.0934	0.2698	0.0325	0.932	0.906
		RESID(-2)^2*(RESID(-2)<0)	-0.0739	0.5167	0.3530		
		GARCH(-1)	0.7419	0.0000	0.0004		
		GARCH(-2)	0.2581	0.1061	0.2184		

Fund: SWE*	E1GARCH-M(1)	sample ind					
Z20	M145	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7952	@SQRT(GARCH)	1.6137	0.3094	0.1180	0.836	0.834
s.e.	1.9210	C	-3.1252	0.2833	0.1155	0.952	0.949
AIC	4.1527	ZHG	0.7227	0.0000	0.0000	0.204	0.208
SBC	4.2513	C(4)	1.1158	0.0000	0.0000	0.308	0.356
J-Bera	0.1333	C(5)	0.1913	0.1195	0.2037	0.411	0.482
		C(6)	-0.1395	0.1517	0.1058	0.283	0.419
						0.316	0.452
						0.354	0.584

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E1GARCH-M(1)+tsq	sample ind					
Z20	M146	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7954	@SQRT(GARCH)	1.6510	0.3093	0.1220	0.861	0.859
s.e.	1.9251	C	-3.1742	0.2860	0.1241	0.949	0.946
AIC	4.1620	ZHG	0.7210	0.0000	0.0000	0.205	0.205
SBC	4.2771	ZHG^2	-0.0012	0.6551	0.7548	0.297	0.340
J-Bera	0.1300	C(5)	1.1144	0.0000	0.0000	0.399	0.469
		C(6)	0.1928	0.1214	0.2049	0.313	0.443
		C(7)	-0.1385	0.1542	0.1107	0.342	0.474
						0.376	0.612

Fund: SWE*	E1GARCH-M(1)+tdm	sample ind					
Z20	M147	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7964	@SQRT(GARCH)	1.7011	0.3131	0.1247	0.859	0.856
s.e.	1.9204	C	-3.1499	0.3058	0.1437	0.929	0.926
AIC	4.1578	ZHG	0.7571	0.0000	0.0000	0.216	0.214
SBC	4.2728	ZHG*ZHG_TM	-0.0751	0.3078	0.3999	0.293	0.333
J-Bera	0.1067	C(5)	1.1099	0.0000	0.0000	0.400	0.471
		C(6)	0.1932	0.1204	0.2136	0.370	0.496
		C(7)	-0.1365	0.1610	0.1192	0.393	0.528
						0.429	0.671

Fund: SWE*	E1GARCH-M(1,1)	sample ind					
Z20	M148	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7947	@SQRT(GARCH)	1.3255	0.3306	0.1136	0.705	0.707
s.e.	1.9284	C	-2.5809	0.2974	0.1099	0.830	0.828
AIC	4.1587	ZHG	0.7258	0.0000	0.0000	0.159	0.176
SBC	4.2737	C(4)	0.8653	0.0382	0.0735	0.254	0.304
J-Bera	0.1367	C(5)	0.1729	0.1424	0.2544	0.334	0.413
		C(6)	-0.1658	0.1011	0.0809	0.183	0.327
		C(7)	0.2042	0.5151	0.5934	0.248	0.417
						0.289	0.523

Fund: SWE*	E1GARCH-M(1,1)+tsq	sample ind					
Z20	M149	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7946	@SQRT(GARCH)	1.2953	0.3267	0.1167	0.678	0.680
s.e.	1.9337	C	-2.4744	0.3016	0.1199	0.786	0.782
AIC	4.1662	ZHG	0.7247	0.0000	0.0000	0.150	0.168
SBC	4.2976	ZHG^2	-0.0022	0.4083	0.5517	0.224	0.277
J-Bera	0.1614	C(5)	0.8166	0.0275	0.1117	0.290	0.377
		C(6)	0.1636	0.1520	0.2933	0.203	0.356
		C(7)	-0.1705	0.0905	0.0871	0.280	0.458
		C(8)	0.2471	0.3776	0.5535	0.322	0.567

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E1GARCH-M(1,1)+tdm	sample ind					
Z20	M150	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7954	@SQRT(GARCH)	1.2391	0.3270	0.1151	0.610	0.612
s.e.	1.9298	C	-2.2150	0.3312	0.1456	0.733	0.729
AIC	4.1604	ZHG	0.7779	0.0000	0.0000	0.152	0.173
SBC	4.2919	ZHG*ZHG_TM	-0.1046	0.1616	0.2157	0.216	0.275
J-Bera	0.1627	C(5)	0.7755	0.0272	0.1206	0.283	0.377
		C(6)	0.1518	0.1631	0.3407	0.239	0.401
		C(7)	-0.1788	0.0759	0.0849	0.327	0.512
		C(8)	0.2827	0.2907	0.4929	0.380	0.622

Fund: SWE*	E1GARCH-M(2,1)	sample ind					
Z20	M151	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7896	@SQRT(GARCH)	0.5701	0.1789	0.1285	0.871	0.866
s.e.	1.9572	C	-1.1316	0.1300	0.0933	0.976	0.904
AIC	4.1401	ZHG	0.6984	0.0000	0.0000	0.596	0.541
SBC	4.2716	C(4)	1.5040	0.0000	0.0000	0.751	0.762
J-Bera	0.2610	C(5)	0.3951	0.0143	0.0011	0.805	0.829
		C(6)	-0.1718	0.0712	0.0216	0.733	0.808
		C(7)	0.2075	0.0778	0.0960	0.593	0.586
		C(8)	-0.6611	0.0000	0.0001	0.673	0.811

Fund: SWE*	E1GARCH-M(2,1)+tsq	sample ind					
Z20	M152	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7866	@SQRT(GARCH)	-0.0239	0.9415	0.9345	0.318	0.317
s.e.	1.9763	C	0.0139	0.9800	0.9772	0.420	0.460
AIC	4.1103	ZHG	0.7104	0.0000	0.0000	0.512	0.575
SBC	4.2582	ZHG^2	-0.0020	0.4447	0.5199	0.679	0.739
J-Bera	0.3033	C(5)	0.6663	0.0000	0.0000	0.262	0.270
		C(6)	-0.0222	0.5986	0.7123	0.272	0.313
		C(7)	-0.0458	0.1559	0.0406	0.298	0.255
		C(8)	1.4306	0.0000	0.0000	0.266	0.263
		C(9)	-0.9775	0.0000	0.0000		

Fund: SWE*	E1GARCH-M(2,1)+tdm	sample ind					
Z20	M153	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7882	@SQRT(GARCH)	0.0135	0.9675	0.9636	0.309	0.309
s.e.	1.9689	C	0.0833	0.8874	0.8620	0.380	0.428
AIC	4.1042	ZHG	0.7612	0.0000	0.0000	0.497	0.570
SBC	4.2521	ZHG*ZHG_TM	-0.1015	0.1710	0.1700	0.666	0.738
J-Bera	0.3276	C(5)	0.6603	0.0000	0.0000	0.356	0.370
		C(6)	-0.0184	0.6550	0.7447	0.403	0.439
		C(7)	-0.0421	0.1744	0.0650	0.399	0.331
		C(8)	1.4302	0.0000	0.0000	0.368	0.339
		C(9)	-0.9771	0.0000	0.0000		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E1GARCH-M(1,2)	sample ind					
Z20	M154	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7962	@SQRT(GARCH)	1.6890	0.1612	0.2122	0.677	0.680
s.e.	1.9262	C	-3.2192	0.1356	0.2103	0.841	0.848
AIC	4.1566	ZHG	0.7381	0.0000	0.0000	0.385	0.391
SBC	4.2881	C(4)	0.7538	0.0276	0.1237	0.550	0.563
J-Bera	0.1825	C(5)	0.1728	0.1049	0.2708	0.632	0.624
		C(6)	-0.1660	0.2111	0.2577	0.434	0.524
		C(7)	-0.1216	0.1151	0.1803	0.542	0.641
		C(8)	0.3851	0.1765	0.3659	0.582	0.669

Fund: SWE*	E1GARCH-M(1,2)+tsq	sample ind					
Z20	M155	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7964	@SQRT(GARCH)	1.6524	0.1444	0.2098	0.720	0.722
s.e.	1.9305	C	-3.0457	0.1295	0.2236	0.838	0.843
AIC	4.1616	ZHG	0.7291	0.0000	0.0000	0.386	0.391
SBC	4.3095	ZHG^2	-0.0031	0.2252	0.3894	0.531	0.554
J-Bera	0.1844	C(5)	0.7300	0.0144	0.1121	0.611	0.607
		C(6)	0.1660	0.1128	0.2843	0.528	0.595
		C(7)	-0.1805	0.1654	0.2363	0.643	0.710
		C(8)	-0.1236	0.1036	0.1716	0.662	0.730
		C(9)	0.4135	0.0922	0.3010		

Fund: SWE*	E1GARCH-M(1,2)+tdm	sample ind					
Z20	M156	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7973	@SQRT(GARCH)	1.5141	0.1675	0.1922	0.716	0.718
s.e.	1.9261	C	-2.6598	0.1716	0.2275	0.853	0.856
AIC	4.1553	ZHG	0.7843	0.0000	0.0000	0.381	0.386
SBC	4.3032	ZHG*ZHG_TM	-0.1128	0.1246	0.1733	0.519	0.547
J-Bera	0.1827	C(5)	0.7216	0.0167	0.1107	0.622	0.630
		C(6)	0.1689	0.1108	0.2928	0.582	0.649
		C(7)	-0.1806	0.1693	0.2316	0.694	0.758
		C(8)	-0.1334	0.0972	0.1526	0.715	0.780
		C(9)	0.4159	0.0891	0.2989		

Fund: SWE*	E1GARCH-M(2,2)	sample ind					
Z20	M157	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7979	@SQRT(GARCH)	1.3505	0.0692	0.0265	0.676	0.678
s.e.	1.9232	C	-2.5448	0.0500	0.0254	0.584	0.610
AIC	4.1345	ZHG	0.7270	0.0000	0.0000	0.680	0.680
SBC	4.2824	C(4)	0.8678	0.0000	0.0000	0.705	0.714
J-Bera	0.0908	C(5)	0.1823	0.0806	0.1449	0.810	0.821
		C(6)	-0.2257	0.0376	0.1168	0.415	0.498
		C(7)	-0.1206	0.0649	0.0849	0.490	0.558
		C(8)	0.9545	0.0000	0.0000	0.491	0.536
		C(9)	-0.6459	0.0003	0.0000		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

E1GARCH-M(2,2)+tsq
M158

Errors generated – model rejected

E1GARCH-M(2,2)+tdm
M159

Errors generated – model rejected

Fund: SWE*	E2GARCH-M(1)	sample ind					
Z20	M160	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7942	@SQRT(GARCH)	1.0719	0.2379	0.1611	0.765	0.763
s.e.	1.9307	C	-2.1100	0.1971	0.1524	0.897	0.896
AIC	4.1572	ZHG	0.7263	0.0000	0.0000	0.173	0.177
SBC	4.2723	C(4)	1.1200	0.0000	0.0000	0.278	0.325
J-Bera	0.1165	C(5)	0.1809	0.1091	0.2613	0.381	0.453
		C(6)	-0.1742	0.0876	0.0576	0.185	0.314
		C(7)	-0.1060	0.2666	0.2130	0.245	0.378
						0.292	0.495

Fund: SWE*	E2GARCH-M(1)+tsq	sample ind					
Z20	M161	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7940	@SQRT(GARCH)	0.9668	0.2468	0.1696	0.743	0.739
s.e.	1.9365	C	-1.8692	0.2136	0.1689	0.880	0.880
AIC	4.1655	ZHG	0.7210	0.0000	0.0000	0.164	0.164
SBC	4.2969	ZHG^2	-0.0018	0.4759	0.6328	0.252	0.294
J-Bera	0.1114	C(5)	1.1220	0.0000	0.0000	0.347	0.420
		C(6)	0.1775	0.1179	0.2876	0.205	0.335
		C(7)	-0.1804	0.0835	0.0514	0.269	0.404
		C(8)	-0.1222	0.2004	0.1805	0.315	0.519

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E2GARCH-M(1)+tdm	sample ind					
Z20	M162	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7946	@SQRT(GARCH)	0.8712	0.2462	0.1696	0.703	0.696
s.e.	1.9336	C	-1.5337	0.2591	0.2078	0.848	0.851
AIC	4.1589	ZHG	0.7742	0.0000	0.0000	0.167	0.164
SBC	4.2904	ZHG*ZHG_TM	-0.1038	0.1506	0.2372	0.243	0.284
J-Bera	0.1133	C(5)	1.1152	0.0000	0.0000	0.340	0.413
		C(6)	0.1780	0.1145	0.3077	0.262	0.396
		C(7)	-0.1855	0.0807	0.0472	0.339	0.478
		C(8)	-0.1483	0.1224	0.1292	0.393	0.591

Fund: SWE*	E2GARCH-M(1,1)	sample ind					
Z20	M163	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7943	@SQRT(GARCH)	1.0839	0.2737	0.1524	0.767	0.766
s.e.	1.9352	C	-2.1287	0.2341	0.1442	0.873	0.872
AIC	4.1666	ZHG	0.7269	0.0000	0.0000	0.166	0.176
SBC	4.2981	C(4)	0.9900	0.0474	0.2437	0.267	0.317
J-Bera	0.1219	C(5)	0.1868	0.1162	0.2491	0.362	0.439
		C(6)	-0.1731	0.0937	0.0592	0.182	0.318
		C(7)	-0.0747	0.5103	0.6052	0.247	0.398
		C(8)	0.0974	0.7939	0.8871	0.293	0.510

Fund: SWE*	E2GARCH-M(1,1)+tsq	sample ind					
Z20	M164	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7941	@SQRT(GARCH)	1.0125	0.2762	0.1521	0.734	0.733
s.e.	1.9413	C	-1.9513	0.2454	0.1504	0.834	0.833
AIC	4.1742	ZHG	0.7242	0.0000	0.0000	0.153	0.163
SBC	4.3221	ZHG^2	-0.0021	0.4098	0.5591	0.235	0.285
J-Bera	0.1414	C(5)	0.9424	0.0229	0.3188	0.316	0.400
		C(6)	0.1804	0.1210	0.2865	0.204	0.349
		C(7)	-0.1804	0.0828	0.0567	0.280	0.441
		C(8)	-0.0800	0.4573	0.6279	0.326	0.552
		C(9)	0.1383	0.6552	0.8577		

Fund: SWE*	E2GARCH-M(1,1)+tdm	sample ind					
Z20	M165	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7948	@SQRT(GARCH)	0.9168	0.2773	0.1579	0.688	0.685
s.e.	1.9380	C	-1.6059	0.2944	0.1935	0.801	0.802
AIC	4.1675	ZHG	0.7789	0.0000	0.0000	0.156	0.166
SBC	4.3154	ZHG*ZHG_TM	-0.1094	0.1404	0.1962	0.227	0.281
J-Bera	0.1447	C(5)	0.9327	0.0128	0.3117	0.312	0.402
		C(6)	0.1795	0.1148	0.3120	0.253	0.406
		C(7)	-0.1858	0.0785	0.0531	0.341	0.508
		C(8)	-0.1025	0.3312	0.5432	0.397	0.617
		C(9)	0.1410	0.6127	0.8525		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E2GARCH-M(2,1)	sample ind					
Z20	M166	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7901	@SQRT(GARCH)	0.4092	0.2259	0.1402	0.129	0.131
s.e.	1.9598	C	-0.8049	0.1547	0.0833	0.148	0.194
AIC	4.0850	ZHG	0.7243	0.0000	0.0000	0.264	0.353
SBC	4.2330	C(4)	0.6423	0.0000	0.0000	0.304	0.372
J-Bera	0.3864	C(5)	-0.1068	0.0307	0.0732	0.103	0.147
		C(6)	-0.1509	0.0001	0.0183	0.018	0.065
		C(7)	0.1311	0.0002	0.0025	0.021	0.031
		C(8)	1.4499	0.0000	0.0000	0.023	0.033
		C(9)	-0.9338	0.0000	0.0000		

Fund: SWE*	E2GARCH-M(2,1)+tsq	sample ind					
Z20	M167	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7911	@SQRT(GARCH)	0.4742	0.1623	0.0784	0.245	0.246
s.e.	1.9604	C	-0.8112	0.1512	0.0685	0.253	0.310
AIC	4.0882	ZHG	0.7239	0.0000	0.0000	0.366	0.466
SBC	4.2525	ZHG^2	-0.0035	0.2571	0.1546	0.483	0.570
J-Bera	0.4649	C(5)	0.6316	0.0000	0.0000	0.230	0.264
		C(6)	-0.1001	0.0402	0.0410	0.100	0.180
		C(7)	-0.1618	0.0000	0.0070	0.092	0.082
		C(8)	0.1448	0.0001	0.0007	0.088	0.084
		C(9)	1.4407	0.0000	0.0000		
		C(10)	-0.9211	0.0000	0.0000		

Fund: SWE*	E2GARCH-M(2,1)+tdm	sample ind					
Z20	M168	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7927	@SQRT(GARCH)	0.5069	0.1455	0.0667	0.262	0.263
s.e.	1.9530	C	-0.7188	0.2309	0.1124	0.287	0.351
AIC	4.0814	ZHG	0.7981	0.0000	0.0000	0.407	0.506
SBC	4.2457	ZHG*ZHG_TM	-0.1335	0.0945	0.0296	0.531	0.614
J-Bera	0.5127	C(5)	0.6217	0.0000	0.0000	0.306	0.348
		C(6)	-0.0927	0.0530	0.0518	0.185	0.286
		C(7)	-0.1600	0.0000	0.0023	0.150	0.128
		C(8)	0.1433	0.0000	0.0001	0.150	0.141
		C(9)	1.4354	0.0000	0.0000		
		C(10)	-0.9164	0.0000	0.0000		

Fund: SWE*	E2GARCH-M(1,2)	sample ind					
Z20	M169	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8134	@SQRT(GARCH)	1.9950	0.0001	0.0081	0.802	0.804
s.e.	1.8478	C	-3.7114	0.0000	0.0064	0.920	0.919
AIC	4.0759	ZHG	0.7034	0.0000	0.0000	0.951	0.946
SBC	4.2238	C(4)	0.0601	0.0000	0.0000	0.968	0.962
J-Bera	0.1810	C(5)	0.1471	0.1891	0.0891	0.977	0.981
		C(6)	-0.1882	0.0954	0.0320	0.881	0.871
		C(7)	-0.1506	0.0442	0.0186	0.767	0.699
		C(8)	0.1052	0.1612	0.0650	0.844	0.807
		C(9)	0.9723	0.0000	0.0000		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	E2GARCH-M(1,2)+tsq	sample ind					
Z20	M170	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7997	@SQRT(GARCH)	2.2775	0.1409	0.1385	0.750	0.752
s.e.	1.9197	C	-4.2208	0.1260	0.1463	0.854	0.866
AIC	4.1638	ZHG	0.7282	0.0000	0.0000	0.383	0.384
SBC	4.3281	ZHG^2	-0.0030	0.2671	0.4218	0.540	0.539
J-Bera	0.3043	C(5)	0.4546	0.1763	0.0616	0.619	0.590
		C(6)	0.1510	0.1012	0.2483	0.518	0.576
		C(7)	-0.1840	0.1298	0.1725	0.632	0.692
		C(8)	-0.1221	0.0998	0.1467	0.626	0.678
		C(9)	0.0994	0.2233	0.2094		
		C(10)	0.6478	0.0253	0.0011		

Fund: SWE*	E2GARCH-M(1,2)+tdm	sample ind					
Z20	M171	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8110	@SQRT(GARCH)	1.3717	0.0000	0.0046	0.652	0.655
s.e.	1.8645	C	-2.4035	0.0000	0.0142	0.805	0.803
AIC	4.0800	ZHG	0.7622	0.0000	0.0000	0.794	0.806
SBC	4.2443	ZHG*ZHG_TM	-0.0912	0.1808	0.2698	0.846	0.844
J-Bera	0.2294	C(5)	0.0872	0.0000	0.0067	0.896	0.905
		C(6)	0.1661	0.0000	0.1089	0.861	0.863
		C(7)	-0.2368	0.0000	0.0276	0.898	0.884
		C(8)	-0.1725	0.0000	0.0100	0.942	0.939
		C(9)	0.1189	0.0000	0.0588		
		C(10)	0.9671	0.0000	0.0000		

Fund: SWE*	E2GARCH-M(2,2)	sample ind					
Z20	M172	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7989	@SQRT(GARCH)	1.5207	0.0583	0.0292	0.625	0.628
s.e.	1.9232	C	-2.8797	0.0389	0.0244	0.514	0.533
AIC	4.1329	ZHG	0.7311	0.0000	0.0000	0.611	0.600
SBC	4.2973	C(4)	0.7421	0.0002	0.0000	0.644	0.649
J-Bera	0.0950	C(5)	0.1345	0.1658	0.2001	0.702	0.713
		C(6)	-0.1872	0.0444	0.1495	0.335	0.427
		C(7)	-0.1485	0.0231	0.0672	0.362	0.416
		C(8)	0.0919	0.2471	0.1415	0.343	0.369
		C(9)	1.0755	0.0000	0.0000		
		C(10)	-0.6638	0.0000	0.0000		

E2GARCH-M(2,2)+tsq
M173

Errors generated – model rejected

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

E2GARCH-M(2,2)+tdm
M174

Errors generated – model rejected

P1ARCH-M(1)
M175

Errors generated – model rejected

P1ARCH-M(1)+tsq
M176

Errors generated – model rejected

P1ARCH-M(1)+tdm
M177

Errors generated – model rejected

Fund: SWE*	P1ARCH-M(1,1)	sample ind					
Z20	M178	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7621	@SQRT(GARCH)	-0.7947	0.3034	0.1536	0.003	0.003
s.e.	2.0813	C	2.7038	0.1536	0.0000	0.010	0.005
AIC	4.4574	ZHG	0.7237	0.0000		0.023	0.014
SBC	4.5889	C(4)	8.7201	0.9040	0.7642	0.046	0.029
J-Bera	0.0000	C(5)	-0.0002	0.7642	0.8797	0.008	0.008
		C(6)	-0.9996	0.8797	0.0000	0.001	0.005
		C(7)	0.9582	0.0000	0.6428	0.001	0.009
		C(8)	5.3353	0.6428		0.002	0.016

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

P1ARCH-M(1,1)+tsq
M179

Errors generated – model rejected

P1ARCH-M(1,1)+tdm
M180

Errors generated – model rejected

P1ARCH-M(2,1)
M181

Errors generated – model rejected

P1ARCH-M(2,1)+tsq
M182

Errors generated – model rejected

Fund: SWE*	P1ARCH-M(2,1)+tdm	sample ind					
Z20	M183	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7935	@SQRT(GARCH)	1.0219	0.0454	0.0601	0.552	0.555
s.e.	1.9488	C	-1.7391	0.0601	0.0000	0.670	0.682
AIC	4.1560	ZHG	0.7904	0.0000	0.1122	0.692	0.729
SBC	4.3203	ZHG*ZHG_TM	-0.1276	0.1122		0.761	0.775
J-Bera	0.0658	C(5)	0.6951	0.7592	0.0000	0.783	0.801
		C(6)	-0.0015	0.0000	0.7901	0.800	0.804
		C(7)	-0.4898	0.7901	0.5565	0.833	0.836
		C(8)	0.5826	0.5565	0.6770	0.895	0.901
		C(9)	0.4038	0.6770	0.3928		
		C(10)	5.4467	0.3928			

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P1ARCH-M(1,2)	sample ind					
Z20	M184	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7940	@SQRT(GARCH)	0.5662	0.4241	0.0454	0.835	0.837
s.e.	1.9416	C	-1.1433	0.3703	0.0230	0.978	0.980
AIC	4.1494	ZHG	0.7302	0.0000	0.0000	0.421	0.437
SBC	4.2973	C(4)	2.7983	0.3220	0.2662	0.588	0.620
J-Bera	0.0847	C(5)	0.1249	0.3325	0.1643	0.709	0.738
		C(6)	0.4551	0.4155	0.1199	0.498	0.603
		C(7)	-0.0588	0.3923	0.3907	0.598	0.691
		C(8)	0.2731	0.3863	0.4443	0.605	0.717
		C(9)	2.3834	0.0926	0.0111		

Fund: SWE*	P1ARCH-M(1,2)+tsq	sample ind					
Z20	M185	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8105	@SQRT(GARCH)	1.4807	0.0000	0.0000	0.000	0.000
s.e.	1.8672	C	-2.7362	0.0000	0.0000	0.000	0.000
AIC	4.1160	ZHG	0.6970	0.0000	0.1331	0.000	0.000
SBC	4.2803	ZHG^2	-0.0037	0.1331		0.000	0.000
J-Bera	0.0000	C(5)	0.0630	0.2011	0.0000	0.000	0.000
		C(6)	0.2425	0.0000	0.1507	0.000	0.000
		C(7)	0.0537	0.1507	0.0000	0.000	0.000
		C(8)	-0.2636	0.0000	0.0000	0.000	0.000
		C(9)	0.9992	0.0000	0.0096		
		C(10)	2.3590	0.0096			

Fund: SWE*	P1ARCH-M(1,2)+tdm	sample ind					
Z20	M186	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7959	@SQRT(GARCH)	0.6799	0.1377	0.0084	0.817	0.818
s.e.	1.9377	C	-1.0578	0.1842	0.0216	0.964	0.968
AIC	4.1408	ZHG	0.8009	0.0000	0.0000	0.427	0.446
SBC	4.3051	ZHG*ZHG_TM	-0.1477	0.0488	0.0601	0.554	0.581
J-Bera	0.1329	C(5)	2.4031	0.2854	0.2407	0.679	0.705
		C(6)	0.1194	0.3774	0.1839	0.700	0.758
		C(7)	0.5306	0.4396	0.1149	0.796	0.845
		C(8)	-0.0679	0.3019	0.2961	0.801	0.865
		C(9)	0.3167	0.2152	0.3921		
		C(10)	2.2474	0.1000	0.0030		

Fund: SWE*	P1ARCH-M(2,2)	sample ind					
Z20	M187	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7901	@SQRT(GARCH)	0.3430	0.6841	0.1051	0.399	0.403
s.e.	1.9652	C	-0.7639	0.6212	0.0354	0.697	0.693
AIC	4.1903	ZHG	0.7400	0.0000	0.0000	0.331	0.338
SBC	4.3547	C(4)	1.4372	0.4517	0.6584	0.474	0.511
J-Bera	0.1537	C(5)	0.0831	0.2374	0.5405	0.519	0.544
		C(6)	-0.0330	0.7172	0.8974	0.326	0.442
		C(7)	-0.0617	0.3238	0.6030	0.408	0.551
		C(8)	0.3899	0.4360	0.5504	0.483	0.615
		C(9)	0.3276	0.4357	0.4463		
		C(10)	2.8578	0.0455	0.0050		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

P1ARCH-M(2,2)+tsq
M188

Errors generated – model rejected

P1ARCH-M(2,2)+tdm
M189

Errors generated – model rejected

Fund: SWE*	P2ARCH-M(1,2)	sample ind					
Z20	M190	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8090	@SQRT(GARCH)	2.4120	0.0001	0.0084	0.603	0.605
s.e.	1.8743	C	-4.3364	0.0000	0.0061	0.764	0.769
AIC	4.0889	ZHG	0.6947	0.0000	0.0000	0.892	0.882
SBC	4.2532	C(4)	0.0352	0.0078	0.0000	0.933	0.914
J-Bera	0.3365	C(5)	0.0545	0.0000	0.0000	0.950	0.952
		C(6)	0.8624	0.2360	0.0627	0.896	0.865
		C(7)	-0.0745	0.0000	0.0000	0.656	0.531
		C(8)	0.4308	0.3639	0.2062	0.742	0.652
		C(9)	0.9929	0.0000	0.0000		
		C(10)	1.1393	0.1003	0.0058		

P2ARCH-M(1,2)+tsq
M191

Errors generated – model rejected

Fund: SWE*	P2ARCH-M(1,2)+tdm	sample ind					
Z20	M192	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7938	@SQRT(GARCH)	0.4665	0.1141	0.0053	0.925	0.925
s.e.	1.9529	C	-0.6919	0.1543	0.0114	0.995	0.995
AIC	4.1485	ZHG	0.7942	0.0000	0.0000	0.436	0.450
SBC	4.3292	ZHG*ZHG_TM	-0.1418	0.0559	0.0688	0.555	0.600
J-Bera	0.1467	C(5)	2.3275	0.1246	0.1297	0.659	0.709
		C(6)	0.0794	0.9746	0.9612	0.609	0.709
		C(7)	0.9812	0.9744	0.9606	0.716	0.804
		C(8)	-0.0194	0.9999	0.9999	0.727	0.838
		C(9)	-0.9995	0.9999	0.9999		
		C(10)	0.2523	0.4748	0.5768		
		C(11)	2.0330	0.0340	0.0001		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	P2ARCH-M(2,2)	sample ind					
Z20	M193	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.8015	@SQRT(GARCH)	2.3871	0.0321	0.0000	0.540	0.544
s.e.	1.9161	C	-4.4123	0.0265	0.0000	0.829	0.830
AIC	4.1572	ZHG	0.7322	0.0000	0.0000	0.356	0.371
SBC	4.3380	C(4)	1.7862	0.4520	0.3447	0.512	0.536
J-Bera	0.4061	C(5)	0.0584	0.4113	0.2107	0.619	0.648
		C(6)	0.1346	0.4806	0.2566	0.544	0.621
		C(7)	-0.0476	0.4513	0.2662	0.619	0.681
		C(8)	0.1937	0.4775	0.1236	0.671	0.752
		C(9)	0.5891	0.0219	0.0417		
		C(10)	0.1105	0.5514	0.5734		
		C(11)	3.0572	0.0914	0.0222		

P2ARCH-M(2,2)+tsq
M194

Errors generated – model rejected

Fund: SWE*	P2ARCH-M(2,2)+tdm	sample ind					
Z20	M195	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7778	@SQRT(GARCH)	1.7069	0.0001	0.0028	0.000	0.000
s.e.	2.0323	C	-2.9758	0.0002	0.0072	0.000	0.000
AIC	4.3265	ZHG	0.6934	0.0000	0.0000	0.000	0.000
SBC	4.5237	ZHG*ZHG_TM	-0.0462	0.5499	0.5019	0.000	0.000
J-Bera	0.0000	C(5)	0.0297	0.3300	0.5662	0.000	0.000
		C(6)	0.0910	0.0240	0.1599	0.000	0.000
		C(7)	0.1263	0.7488	0.7425	0.000	0.000
		C(8)	-0.0106	0.6695	0.8959	0.000	0.000
		C(9)	-0.9961	0.2521	0.7678		
		C(10)	0.7403	0.0393	0.5885		
		C(11)	0.1741	0.6219	0.8910		
		C(12)	0.6894	0.0145	0.0246		

Fund: SWE*	COMP	sample ind					
Z20	M196	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7869	C	-0.1020	0.4331	0.3673	0.953	0.953
s.e.	1.9646	ZHG	0.7286	0.0000	0.0000	0.692	0.695
AIC	4.0924	C(3)	3.2216	0.0000	0.0000	0.279	0.296
SBC	4.2075	C(4)	0.9824	0.0000	0.0000	0.427	0.472
J-Bera	0.8860	C(5)	-0.0521	0.0001	0.1152	0.506	0.576
		C(6)	0.1277	0.0881	0.1851	0.319	0.430
		C(7)	-0.0505	0.9051	0.8923	0.406	0.508
						0.506	0.610

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	COMP+tsq	sample ind					
Z20	M197	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7867	C	-0.1181	0.3722	0.4100	0.368	0.368
s.e.	1.9705	ZHG	0.7237	0.0000	0.0000	0.501	0.499
AIC	4.1784	ZHG^2	-0.0019	0.4632	0.5939	0.571	0.547
SBC	4.3099	C(4)	3.6321	0.0000	0.0000	0.698	0.712
J-Bera	0.0671	C(5)	0.3083	0.7932	0.9267	0.636	0.614
		C(6)	-0.6007	0.9609	0.9851	0.402	0.433
		C(7)	0.7192	0.9531	0.9822	0.375	0.473
		C(8)	-0.5416	0.9607	0.9852	0.447	0.534

Fund: SWE*	COMP+tdm	sample ind					
Z20	M198	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7881	C	0.0968	0.6449	0.5858	0.498	0.497
s.e.	1.9640	ZHG	0.7811	0.0000	0.0000	0.709	0.696
AIC	4.1720	ZHG*ZHG_TM	-0.1205	0.1037	0.1557	0.612	0.589
SBC	4.3034	C(4)	3.5865	0.0000	0.0000	0.716	0.744
J-Bera	0.0447	C(5)	0.3572	0.7575	0.9001	0.707	0.707
		C(6)	-0.6753	0.9657	0.9849	0.574	0.611
		C(7)	0.8134	0.9587	0.9819	0.553	0.643
		C(8)	-0.5672	0.9688	0.9864	0.619	0.723

Fund: SWE*	ASCO	sample ind					
Z20	M199	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7869	C	-0.1074	0.4061	0.3603	0.832	0.833
s.e.	1.9695	ZHG	0.7333	0.0000	0.0000	0.896	0.889
AIC	4.1068	C(3)	3.1904	0.0000	0.0000	0.223	0.239
SBC	4.2382	C(4)	0.9831	0.0000	0.0000	0.350	0.396
J-Bera	0.9419	C(5)	-0.0434	0.0000	0.0825	0.431	0.487
		C(6)	0.0244	0.7533	0.7682	0.390	0.501
		C(7)	0.2143	0.1763	0.1534	0.487	0.593
		C(8)	-0.0225	0.9393	0.9500	0.555	0.672

Fund: SWE*	ASCO+tsq	sample ind					
Z20	M200	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7857	C	-0.0207	0.8789	0.8648	0.553	0.552
s.e.	1.9803	ZHG	0.7284	0.0000	0.0000	0.690	0.687
AIC	4.1576	ZHG^2	-0.0053	0.0425	0.0000	0.467	0.446
SBC	4.3055	C(4)	3.6004	0.0000	0.0000	0.636	0.650
J-Bera	0.1385	C(5)	0.5723	0.0041	0.0002	0.650	0.632
		C(6)	-0.1590	0.3915	0.0349	0.583	0.623
		C(7)	0.1251	0.5624	0.1498	0.624	0.692
		C(8)	0.3585	0.0178	0.0367	0.602	0.667
		C(9)	0.0383	0.8672	0.8659		

Table B-2: SWE* Candidate Models With 'Best' E2GARCH(2,2)+tdm Highlighted (continued)

Fund: SWE*	ASCO+tdm	sample ind					
Z20	M201	Coefficient	Estimate	p-value	p-robust	Q-stat	LM
R-sq	0.7883	C	0.1199	0.5436	0.4733	0.816	0.816
s.e.	1.9684	ZHG	0.7883	0.0000	0.0000	0.713	0.708
AIC	4.1038	ZHG*ZHG_T M	-0.1254	0.0754	0.0687	0.150	0.168
SBC	4.2517	C(4)	2.8568	0.0000	0.0000	0.256	0.308
J-Bera	0.8354	C(5)	0.9792	0.0000	0.0000	0.344	0.419
		C(6)	-0.0476	0.0423	0.1318	0.373	0.487
		C(7)	-0.0085	0.9167	0.9269	0.448	0.554
		C(8)	0.2795	0.0951	0.0863	0.501	0.633
		C(9)	0.1475	0.7453	0.6121		

Appendix C: Information Criteria and GARCH Model Selection

The use of information criteria in GARCH model selection (see section 5.6.3 on p.85) has been shown to produce biased results; this requires discussion in the context of the present research.

Consider the Akaike information criterion (*AIC*). As actually calculated by the Eviews 5.1 software, this is

$$AIC_{\text{Eviews}} = -2l/\mathrm{T} + 2\mathrm{k}/\mathrm{T} \tag{25}$$

where T is the number of observations, k is the number of parameters estimated and *l* is the value of the log likelihood function given by

$$l = -\frac{\mathrm{T}}{2}\left(1 + \log 2\pi + \log\left(RSS/\mathrm{T}\right)\right) \tag{26}$$

where *RSS* is the sum of the squared residuals referred to in section 5.6.3 on p.85. Substituting (26) into (25) and rearranging gives

$$AIC_{\text{Eviews}} = 1 + \log 2\pi + \log RSS - \log \mathrm{T} + 2\mathrm{k}/\mathrm{T} \tag{27}$$

Comparing (27) with the AIC reported in the main text in equation (22) on p.85, repeated here for convenience

$$AIC_{thesis} = \mathrm{T}\log RSS + 2\mathrm{k} \tag{22}$$

it can be seen that (22) is obtained from (27) by multiplying by T and omitting constant terms. Thus (for a given sample size, T) equations (22) and (27) will each have a minimum at the same values of *RSS* and k. Equation (22) simply omits 'clutter' that does not influence the outcome.

This establishes that the Eviews 5.1 software utilises essentially the same conventional *AIC* reported in section 5.6.3 on p.85, bearing in mind Enders' (2004) comment that "Although there are several different ways to report the criteria..., all will select the same model" (p.69).

The Eviews software version 5.1 does not vary the way that *AIC* is calculated when estimating a model of the GARCH type. This is unfortunate, as according to Brooks and Burke (2003) employing *AIC* as per equation (22) in the selection of GARCH models – where now number of parameters k includes the parameters in the variance equation also – "leads to inevitable and critical biases" (p.559).

Brooks and Burke (2003) report yet another slightly-amended-but-effectively-the-same conventional Akaike information criterion:

$$AIC = T\log\hat{\sigma}^2 + 2k \qquad (28)$$

which again will select the same model since estimated model variance $\hat{\sigma}^2$ is calculated as *RSS/T*.

However, Brooks and Burke show that in the case of a GARCH-type model, since the estimated parameters of the mean and variance equations are asymptotically independent, $\hat{\sigma}^2$ does not vary systematically with different variance equation specifications. Thus minmising *AIC* as calculated in equation (28) – or, equivalently, equations (22) or (27) – will tend to select models with minimum k. In the present research, this means that GARCH(1,1) models will be over-selected, as alternatives involve estimation of more parameters.

Brooks and Burke go on to show that a modified form of *AIC* is valid when selecting amongst GARCH-type models, which they denote *HAIC*:

$$HAIC = \sum_{t=1}^{T}\log\tilde{\sigma}_t^{\,2} + 2k \qquad (29)$$

In equation (29) $\tilde{\sigma}_t^{\,2}$ is the conditional variance estimated at time t by the method of maximum likelihood, as is commonly done with GARCH-type models. Note that if in fact the variance is constant over time, *HAIC* in (29) reduces to (28), the conventional *AIC*.

Since *AIC* and not *HAIC* was used in the present research, the results are asymptotically biased towards over-selection of GARCH(1,1) models. Given the above, the frequency of selection of GARCH(1,1) and alternatives with more parameters is of interest. Time sample x12 contains the largest number of funds estimated over a common time period. Allowing for the fact that a peer may be a peer to more than one ethical fund, there are 62 distinct funds in time sample x12. The models selected as 'best' for these 62 funds are listed in Table C-1.

Table C-1: Selected Model Frequency (time sample x12, CAPM, own benchmark)

Model	frequency
GARCH(1,1)	10
GARCH(2,1)	6
ARCH(1)	4
GARCH-M(2,1)	4
E1GARCH(2,1)	4
E1GARCH(2,2)	3
T1ARCH(1,1)	3
E1GARCH(1,1)	2
E1GARCH(2,2)	2
E2GARCH(1,1)	2
E2GARCH(2,2)	2
T1ARCH(2,2)	2
T1ARCH-M(1,1)	2
ASCO	2
GARCH(2,2)	1
GARCH(1,2)	1
E1GARCH(1)	1
E2GARCH(1,1)	1
T1ARCH(2,1)	1
T1ARCH(1,2)	1
GARCH-M(1,1)	1
E1GARCH-M(1)	1
E1GARCH-M(2,2)	1
E2GARCH-M(1,1)	1
T1ARCH-M(2,1)	1
E2GARCH-M(2,2)	1
T2ARCH-M(1,1)	1
COMP	1

While it is true that GARCH(1,1) is the commonest model selected (16% of the total) Table C-1 is not suggestive of serious bias towards GARCH(1,1) and neglect of models with more parameters.

While the logic of Brooks and Burke (2003) appears correct, the question of the size of such bias and its significance in particular applications is only partially addressed in their paper. Neglect of models other than GARCH(1,1) does not appear to be an important feature of the present research. Indeed, use of GARCH models of <u>any</u>

variety is novel in the analysis of the performance of ethical funds, so that consideration of only GARCH(1,1) would nonetheless be of interest. Arguably, also, under-selection of alternatives to GARCH(1,1) is preferable to the common practice of ignoring such alternatives altogether.

This appendix has therefore highlighted an important consideration for future research in this area, but nonetheless there is little to suggest that the results of the present research are affected in important ways by the asymptotic bias shown by Brooks and Burke (2003) to be present.

Appendix D: Example Eviews 5.1 Batch Program

The following pages illustrate the Eviews 5.1 program code by which the methods described in chapter 4, Methods of Analysis, from p.53 onwards are implemented. In practice, program details are varied as circumstances vary – this is an illustrative example only.

```
'================================
'SEE SECTION LIKE THIS BELOW FOR
'PROGRAM IN USE - SUBROUTINES 1st
'================================

        subroutine make_output_table
        d yrls_F!f*
        table(12,10) y_f!fmod_{%s}_om
        setcolwidth(y_f!fmod_{%s}_om,1,11)
        setcolwidth(y_f!fmod_{%s}_om,2,18)
        setcolwidth(y_f!fmod_{%s}_om,3,1)
        setcolwidth(y_f!fmod_{%s}_om,5,8)
        setcolwidth(y_f!fmod_{%s}_om,6,8)
        setcolwidth(y_f!fmod_{%s}_om,7,8)
        setcolwidth(y_f!fmod_{%s}_om,8,1)
        setcolwidth(y_f!fmod_{%s}_om,9,8)
        setcolwidth(y_f!fmod_{%s}_om,10,8)
        setcolwidth(y_f!fmod_{%s}_om,11,8)
        endsub

        subroutine make_bestout_table
'declare new interim table for best aic and sic models only
'has same formatting as above.
        table(12,10) y_asmin_{%s}_om
        setcolwidth(y_asmin_{%s}_om,1,11)
        setcolwidth(y_asmin_{%s}_om,2,18)
        setcolwidth(y_asmin_{%s}_om,3,1)
        setcolwidth(y_asmin_{%s}_om,5,8)
        setcolwidth(y_asmin_{%s}_om,6,8)
        setcolwidth(y_asmin_{%s}_om,7,8)
        setcolwidth(y_asmin_{%s}_om,8,1)
        setcolwidth(y_asmin_{%s}_om,9,8)
        setcolwidth(y_asmin_{%s}_om,10,8)
        setcolwidth(y_asmin_{%s}_om,11,8)
'also need similar table for output after choosing between min aic
'and min sic models according to min se - this is the 'real' output!
        table(12,10) y_bestmod_{%s}_om
        setcolwidth(y_bestmod_{%s}_om,1,11)
        setcolwidth(y_bestmod_{%s}_om,2,18)
        setcolwidth(y_bestmod_{%s}_om,3,1)
        setcolwidth(y_bestmod_{%s}_om,5,8)
        setcolwidth(y_bestmod_{%s}_om,6,8)
        setcolwidth(y_bestmod_{%s}_om,7,8)
        setcolwidth(y_bestmod_{%s}_om,8,1)
        setcolwidth(y_bestmod_{%s}_om,9,8)
```

```
        setcolwidth(y_bestmod_{%s}_om,10,8)
        setcolwidth(y_bestmod_{%s}_om,11,8)
        for !i = 1 to 169
        setline(y_bestmod_{%s}_om,14*!i)
        next
'also a table to note where aic and sic select the same model for a fund
'use separate table for each sample spec (all, ind, x4, x8, x12)
        for !r = 1 to 169
        table y_agree_{%s}_om(!r,1) = 0
        next
'also later, a table for holding standard errors of best regression models
'use separate table for each sample spec (all, ind, x4, x8, x12)
        table y_stand_errs_{%s}_om
        endsub

        subroutine modelskip
'insert fake high inf criteria of 50 in output table
        setcell(y_f!fmod_{%s}_om,top+4,2, 50,4,"r")
        setcell(y_f!fmod_{%s}_om,top+5,2, 50,4,"r")
'leave blank rows in output table for non-estimated model
        setline(y_f!fmod_{%s}_om,top+13)
'skipped models don't have any cond var series,
'so create fake one here so if condition in infcriteria loop works
        series cv_f!f_m!m_{%s}_om
'also skip subroutine out_arch where intermediate objects are deleted
'so insert the missed commands here...
        d tab1
        d rob*
        endsub

        subroutine out_ls
'just calls others in turn, saves repetition
'OLS version - no variance equation output
        call basicinfo
        call coefinfo
        call qstats
        call archlm
        endsub

        subroutine out_arch
'just calls others in turn, saves repetition
'GARCH version - with variance equation output
'This subroutine includes checking for singular covariance warning in output
'as this does not generate an error message, and skips such models
'set skip paramater initially to no-skip value
        !a = 0
'then check for singular covariance warning, should skip model
        for !i = 4 to 15
        %warning = tab1(!i,1)
        if %warning = "WARNING: Singular covariance - coefficients are not unique" then
        !a = 1
        else
'if no warning is found, then !a remains = 0
        endif
        next
'if warning is found...
        if !a = 1 then
```

```
'a bit of housekeeping that is missed if modelskip is called here
'delete intermediate tables...
        d tab1
        d rob*
'..and .skip results for this model
        call modelskip
        else
'if no warning is found (!a remains = 0) then store model output as usual
        call basicinfo
        call coefinfo
        call varinfo
        call qstats
        call archlm
        endif
        endsub

        subroutine basicinfo
'find first row of mean coef output (_mcoeffstart)
        for !i = 7 to 16
        %tabtext = tab1(!i,2)
        if %tabtext = "Coefficient" then
        scalar _mcoeffstart = !i+2
        endif
        next
'table zmodel_om contains # of mean coeffs
        scalar _mcoeffs = @val(zmodel_om(!m,5))
'so identify last row of mean coef output
        scalar _mcoeffend = _mcoeffstart + _mcoeffs - 1
'find row where R-sq and other output starts
        for !i = 12 to 40
        %tabtext = tab1(!i,1)
        if %tabtext = "R-squared" then
        scalar _rsqrow = !i
        endif
        next
'copy basic info along top row of output table
'dependent variable
'[commenting out old stuff, followed by new stuff]
        %str1 = @right(tab1(1,1),4)
'combine with benchmark preceded by space
'       %str2 = "  " + %bm
'       y_f!fmod_{%s}_om(top,1) = %str1 + %str2
        y_f!fmod_{%s}_om(top,1) = "Fund: " + zfundnames(!f,1)
        y_f!fmod_{%s}_om(top+1,1) = %str1
'sample [commented out]
'       %str1 = @right(tab1(4,1),15)
'       y_f!fmod_{%s}_om(top,4) = %str1
        y_f!fmod_{%s}_om(top,4) = "sample " + %s
'number of observations included [commented out]
'       %str1 = @mid(tab1(5,1),24,13)
'       y_f!fmod_{%s}_om(top,6) = "# of obs " + %str1
'copy R-sq with label
        y_f!fmod_{%s}_om(top+2,1) = "R-sq"
        scalar _rsq = @val(tab1(_rsqrow,2))
        setcell(y_f!fmod_{%s}_om, top+2,2, _rsq,4,"r")
'same for se
        y_f!fmod_{%s}_om(top+3,1) = "s.e."
```

```
        scalar _se = @val(tab1(_rsqrow+2,2))
        setcell(y_f!fmod_{%s}_om,top+3,2, _se,4,"r")
'same for Akaike
        y_f!fmod_{%s}_om(top+4,1) = "AIC"
        scalar _ak = @val(tab1(_rsqrow+2,5))
        setcell(y_f!fmod_{%s}_om,top+4,2, _ak,4,"r")
'same for Schwarz
        y_f!fmod_{%s}_om(top+5,1) = "SBC"
        scalar _sh = @val(tab1(_rsqrow+3,5))
        setcell(y_f!fmod_{%s}_om,top+5,2, _sh,4,"r")
'similar for Jarque Bera normality test
        y_f!fmod_{%s}_om(top+6,1) = "J-Bera"
'make series of standardized resids
        eq_F!f_M!m.makeresids(s) _stanres
        freeze(tab3) _stanres.stats
        scalar _jbp = @val(tab3(15,2))
        setcell(y_f!fmod_{%s}_om,top+6,2, _jbp,4,"r")
        d tab3
        d _stanres
' some simple formatting before next stage
        For !i = top+1 to top+9
        y_f!fmod_{%s}_om(!i,3) = "|"
        next
'insert headings for coefs and p-values
        y_f!fmod_{%s}_om(top+1,4) = "Coefficient"
        y_f!fmod_{%s}_om(top+1,5) = "Estimate"
        y_f!fmod_{%s}_om(top+1,6) = "p-value"
        y_f!fmod_{%s}_om(top+1,7) = "p-robust"
        endsub

        subroutine coefinfo
'set top offset for first loop
        !a = 2
        for !i = _mcoeffstart to _mcoeffend
        y_f!fmod_{%s}_om(top+!a,4) = tab1(!i,1)
        scalar _c = @val(tab1(!i,2))
        setcell(y_f!fmod_{%s}_om,top+!a,5, _c,4)
        y_f!fmod_{%s}_om(top+!a,6) = tab1(!i,5)
        y_f!fmod_{%s}_om(top+!a,7) = rob_tab1(!i+1,5)
'increment top offset before exiting loop
        !a = !a + 1
        next
        endsub

        subroutine varinfo
'variance output starts 4 rows below mean output...
        scalar _vcoeffstart = _mcoeffend+4
'... and ends depending on garch model specification
        scalar _vcoeffend = _rsqrow-2
        for !i = _vcoeffstart to _vcoeffend
'offset !a OK from previous subroutine coefinfo
        y_f!fmod_{%s}_om(top+!a,4) = tab1(!i,1)
        scalar _c = @val(tab1(!i,2))
        setcell(y_f!fmod_{%s}_om,top+!a,5, _c,4)
        y_f!fmod_{%s}_om(top+!a,6) = tab1(!i,5)
        y_f!fmod_{%s}_om(top+!a,7) = rob_tab1(!i+1,5)
'increment top offset before exiting loop
```

```
        !a = !a + 1
        next
'delete intermediate tables
        d tab1
        d rob*
        endsub

        subroutine qstats
        freeze(tab2) eq_F!f_M!m.correlsq
        y_f!fmod_{%s}_om(top+1,9) = "Q-stat"
        for !i = 2 to 9
        y_f!fmod_{%s}_om(top+!i,9) = tab2(!i+5,7)
        next
        For !i = top+1 to top+9
        y_f!fmod_{%s}_om(!i,8) = "|"
        next
        d tab2
        d rob*
        endsub

        subroutine archlm
        y_f!fmod_{%s}_om(top+1,10) = "LM"
        for !i = 1 to 8
        freeze(tab5) eq_F!f_M!m.archtest(!i)
        scalar _archp = @val(tab5(4,5))
        setcell(y_f!fmod_{%s}_om,top+1+!i,10,_archp,3)
        d tab5
        next
'some tidying up before next model (but retaining _mcoeffstart)
        scalar keep = _mcoeffstart
        d tab*
        d _*
        scalar _mcoeffstart = keep
        d keep
'note - if need more rows change next 2 lines
'also check subroutine modelskip!!!
        endsub

        subroutine infcriteria
'finds lowest AIC, SBC and corresponding models
'copies output of these into table y_asmin_{%s}_om
'fill y_asmin_{%s}_om initially with results for model 4 for current fund
'(1st GARCH model - ols no good, want cond var series (cvar))
'unless current fund is z2, 30, 70, 84 - needs different default model
        if (!f = 2) or (!f = 45) or (!f = 61) or (!f = 90) or (!f = 110) or (!f = 125) or (!f = 139) or (!f =
148) or (!f = 163) then
'for these funds only default is m62 (line 854+) not m4
'first time m62 as placeholder for best AIC model...
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28),!c) = y_f!fmod_{%s}_om(!r+854,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14)
'...and 14 rows below this, repeat model 4 for current
'fund as a placeholder for best SBC model
```

```
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28)+14,!c) = y_f!fmod_{%s}_om(!r+854,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14+14)
'set kept best eqns, cv and r2 initially as model #4 (first garch model)
        copy eq_F!f_M62 y_F!feq_{%s}_om_a
        copy eq_F!f_M62 y_F!feq_{%s}_om_s
        copy cv_f!f_M62_{%s}_om y_F!fcv_{%s}_om_a
        copy cv_f!f_M62_{%s}_om y_F!fcv_{%s}_om_s
'       copy r2_F!f_M62_{%s}_om y_F!fr2_{%s}_om_a
'       copy r2_F!f_M62_{%s}_om y_F!fr2_{%s}_om_s
        endif
'set different default equation for fund 1 only
        if (!f = 1) then 'for this fund only default is m17 (line 224+) not m4
'first time m17 as placeholder for best AIC model...
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28),!c) = y_f!fmod_{%s}_om(!r+224,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14)
'...and 14 rows below this, repeat model 17 for current
'fund as a placeholder for best SBC model
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28)+14,!c) = y_f!fmod_{%s}_om(!r+224,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14+14)
'set kept best eqns, cv and r2 initially as model #4 (first garch model)
        copy eq_F!f_M17 y_F!feq_{%s}_om_a
        copy eq_F!f_M17 y_F!feq_{%s}_om_s
        copy cv_f!f_M17_{%s}_om y_F!fcv_{%s}_om_a
        copy cv_f!f_M17_{%s}_om y_F!fcv_{%s}_om_s
'       copy r2_F!f_M17_{%s}_om y_F!fr2_{%s}_om_a
'       copy r2_F!f_M17_{%s}_om y_F!fr2_{%s}_om_s
        endif
'set different default equation for funds 30 = 70 = 84 only
        if (!f = 30) or (!f = 70) or (!f = 84) then
'for these funds only default is m55 (line 757+) not m4
'first time m55 as placeholder for best AIC model...
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28),!c) = y_f!fmod_{%s}_om(!r+757,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14)
'...and 14 rows below this, repeat model 55 for current
'fund as a placeholder for best SBC model
        for !r = 1 to 13
        for !c = 1 to 11
```

```
        y_asmin_{%s}_om(!r+((!f-1)*28)+14,!c) = y_f!fmod_{%s}_om(!r+757,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14+14)
'set kept best eqns, cv and r2 initially as model #4 (first garch model)
        copy eq_F!f_M55 y_F!feq_{%s}_om_a
        copy eq_F!f_M55 y_F!feq_{%s}_om_s
        copy cv_f!f_M55_{%s}_om y_F!fcv_{%s}_om_a
        copy cv_f!f_M55_{%s}_om y_F!fcv_{%s}_om_s
'       copy r2_F!f_M55_{%s}_om y_F!fr2_{%s}_om_a
'       copy r2_F!f_M55_{%s}_om y_F!fr2_{%s}_om_s
        endif
'... and for the remaining funds... set default as m4
        if (!f <> 1) and (!f <> 2) and (!f <> 30) and (!f <> 45) and (!f <> 61) and (!f <> 70) and (!f
<> 84) and (!f <> 90) and (!f <> 110) and (!f <> 125) and (!f <> 139) and (!f <> 148) and (!f <>
163) then
'or else - set default as m4 for all other funds
'i.e. from y_f!fmod_{%s}_om rows 43 to 55
'start filling y_asmin_{%s}_om at row a multiple of 28 rows down
'first time m4 as placeholder for best AIC model...
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28),!c) = y_f!fmod_{%s}_om(!r+42,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14)
'...and 14 rows below this, repeat model 4 for current
'fund as a placeholder for best SBC model
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28)+14,!c) = y_f!fmod_{%s}_om(!r+42,!c)
        next
        next
'can't copy line between tables, so insert new one
        setline(y_asmin_{%s}_om,((!f-1)*28)+14+14)
'set kept best eqns, cv and r2 initially as model #4 (first garch model)
        copy eq_F!f_M4 y_F!feq_{%s}_om_a
        copy eq_F!f_M4 y_F!feq_{%s}_om_s
        copy cv_f!f_M4_{%s}_om y_F!fcv_{%s}_om_a
        copy cv_f!f_M4_{%s}_om y_F!fcv_{%s}_om_s
'       copy r2_F!f_M4_{%s}_om y_F!fr2_{%s}_om_a
'       copy r2_F!f_M4_{%s}_om y_F!fr2_{%s}_om_s
'end of default model setting if-else condition
        endif
'NOW START COMPARISONS
'set initial infa and infs from model 4, 1st garch in output table
'except for funds 2 and 30 etc...
        if (!f = 2) or (!f = 45) or (!f = 61) or (!f = 90) or (!f = 110) or (!f = 125) or (!f = 139) or (!f =
148) or (!f = 163) then
        scalar infa = @val(y_f!fmod_{%s}_om(859, 2))
        scalar infs = @val(y_f!fmod_{%s}_om(860, 2))
        endif
        if (!f = 30) or (!f = 70) or (!f = 84) then
        scalar infa = @val(y_f!fmod_{%s}_om(761, 2))
        scalar infs = @val(y_f!fmod_{%s}_om(762, 2))
```

```
        endif
        if (!f = 1) then
        scalar infa = @val(y_f!fmod_{%s}_om(229, 2))
        scalar infs = @val(y_f!fmod_{%s}_om(230, 2))
        endif
        if (!f <> 1) and (!f <> 2) and (!f <> 30) and (!f <> 45) and (!f <> 61) and (!f <> 70) and (!f
<> 84) and (!f <> 90) and (!f <> 110) and (!f <> 125) and (!f <> 139) and (!f <> 148) and (!f <>
163) then
        scalar infa = @val(y_f!fmod_{%s}_om(47, 2))
        scalar infs = @val(y_f!fmod_{%s}_om(48, 2))
        endif
'compare initial with each current !i model (subtract)
'start comparison at model 5 i.e. omit ols and initialised m4
        For !i = 4 to !m-1
'note !m is the highest model # estimated in subroutine analysis
'so this says - work through each model from 5 onwards...
'PREPARING IF CONDITION FOR AIC...
'will check if current AIC is lower (!d will be positive) i.e. do nothing if !da<=0
        !da = infa - @val(y_f!fmod_{%s}_om(5+((!i-1)*14), 2))
'and do nothing if any of the Q and LM values are < 0.05 or are NA
        for !q = 1 to 8
        scalar _q!q = @val(y_f!fmod_{%s}_om(3+(!q-1)+((!i-1)*14), 9))
        scalar _lm!q = @val(y_f!fmod_{%s}_om(3+(!q-1)+((!i-1)*14), 10))
        next
'create a scalar to summarise the Q and LM result
        scalar _qlm
'if result is problematic, set _qlm equal to 1, if OK set equal to zero
        if _q1<.05 or _q2<.05 or _q3<.05 or _q4<.05 or _q5<.05 or _q6<.05 or _q7<.05 or
_q8<.05 or _lm1<.05 or _lm2<.05 or _lm3<.05 or _lm4<.05 or _lm5<.05 or _lm6<.05 or
_lm7<.05 or _lm8<.05 or _q1=na or _q2=na or _q3=na or _q4=na or _q5=na or _q6=na or
_q7=na or _q8=na or _lm1=na or _lm2=na or _lm3=na or _lm4=na or _lm5=na or _lm6=na or
_lm7=na or _lm8=na then
        _qlm = 1
        else
        _qlm = 0
        endif
'and do nothing if any value of cv > 1000000 etc... (now not used in if condition)
        scalar _cvmax!i_a = @max(cv_f!f_m!i_{%s}_om)
'will need scalar from table zasym, row of asym coeffs
'use to check asym p-value if this is present, ignore model if p<0.05
        if @val(zasym(!i,2)) > 0 then
        scalar _a1 = @val(zasym(!i,2))
        else
'if asym coeff is not present, check beta p-value, always <0.05, so don't ignore model!
'position of asym coeff(s) is one row down if model is arch-m, see table zaim
        if zaim(!i,1) = 0 then
        scalar _a1 = 4
        endif
        if zaim(!i,1) = 1 then
        scalar _a1 = 5
        endif
        endif
        if @val(zasym(!i,3)) > 0 then
        scalar _a2 = @val(zasym(!i,3))
        else
        if zaim(!i,1) = 0 then
        scalar _a2 = 4
```

```
        endif
        if zaim(!i,1) = 1 then
        scalar _a2 = 5
        endif
        endif
'make scalar for use in testing for significant 2nd order arch coeffs in if condition
        scalar _a2row = @val(za2(!i,1))
'also scalar for use in testing for significant highest order garch coeffs in if condition
        scalar _grow = @val(zgch(!i,1))

'AIC IF CONDITION
        if !da <= 0 or _qlm = 1 or (zaim(!i,1)=1 and @val(y_f!fmod_{%s}_om(7+(14*(!i-
1)),2))>0.05 and @val(y_f!fmod_{%s}_om(3+(14*(!i-1)),6))>0.05) or (zaim(!i,1)=1 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and @val(y_f!fmod_{%s}_om(3+(14*(!i-
1)),7))>0.05) or (ztm(!i,1)=1 and zaim(!i,1)=0 and @val(y_f!fmod_{%s}_om(7+(14*(!i-
1)),2))>0.05 and @val(y_f!fmod_{%s}_om(5+(14*(!i-1)),6))>0.05) or (ztm(!i,1)=1 and
zaim(!i,1)=0 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(5+(14*(!i-1)),7))>0.05) or (ztm(!i,1)=1 and zaim(!i,1)=1 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(6+(14*(!i-
1)),6))>0.05) or (ztm(!i,1)=1 and zaim(!i,1)=1 and @val(y_f!fmod_{%s}_om(7+(14*(!i-
1)),2))<0.05 and @val(y_f!fmod_{%s}_om(6+(14*(!i-1)),7))>0.05) or (_a1>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_a1+(14*(!i-
1)),6))>0.05) or (_a1>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_a1+(14*(!i-1)),7))>0.05) or (_a2>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_a2+(14*(!i-
1)),6))>0.05) or (_a2>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_a2+(14*(!i-1)),7))>0.05) or (za2(!i,1)>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_a2row+(14*(!i-
1)),6))>0.05) or (za2(!i,1)>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_a2row+(14*(!i-1)),7))>0.05) or (zgch(!i,1)>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_grow+(14*(!i-
1)),6))>0.05) or (zgch(!i,1)>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_grow+(14*(!i-1)),7))>0.05) then

'...when conditionkeep is true - keep initial AIC (do nothing)
        else
'when condition is false (current AIC lower)...
'update infa, eqn, cv and r2,
'replace eqn for keeping with one for current lower aic model
        infa = @val(y_f!fmod_{%s}_om((5+((!i-1)*14)), 2))
        d y_F!feq_{%s}_om_a
        copy eq_F!f_M!i y_F!feq_{%s}_om_a
        copy cv_f!f_M!i_{%s}_om y_F!fcv_{%s}_om_a
'       copy r2_F!f_M!i_{%s}_om y_F!fr2_{%s}_om_a
'overwite bestout for this model with lower AIC model
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+((!f-1)*28),!c) = y_f!fmod_{%s}_om((!r+((!i-1)*14)),!c)
        next
        next
        endif
'PREPARING IF CONDITION FOR SBC...
'both in same !i loop so _q and _lm overwritten, don't need _a then _s
'will check if current SBC is lower (!d will be positive) i.e. do nothing if !ds<=0
        !ds = infs - @val(y_f!fmod_{%s}_om(6+((!i-1)*14), 2))
'and do nothing if any of the Q and LM values are < 0.05 or are NA
        for !q = 1 to 8
```

```
        scalar _q!q = @val(y_f!fmod_{%s}_om(3+(!q-1)+((!i-1)*14), 9))
        scalar _lm!q = @val(y_f!fmod_{%s}_om(3+(!q-1)+((!i-1)*14), 10))
        next
'and do nothing if any value of cv > 1000000 etc...
        scalar _cvmax!i_s = @max(cv_f!f_m!i_{%s}_om)
'       scalar _r2max!i_s = @max(r2_F!f_M!i_{%s}_om)
'SBC IF CONDITION
        if !ds <= 0 or _qlm = 1 or (zaim(!i,1)=1 and @val(y_f!fmod_{%s}_om(7+(14*(!i-
1)),2))>0.05 and @val(y_f!fmod_{%s}_om(3+(14*(!i-1)),6))>0.05) or (zaim(!i,1)=1 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and @val(y_f!fmod_{%s}_om(3+(14*(!i-
1)),7))>0.05) or (ztm(!i,1)=1 and zaim(!i,1)=0 and @val(y_f!fmod_{%s}_om(7+(14*(!i-
1)),2))>0.05 and @val(y_f!fmod_{%s}_om(5+(14*(!i-1)),6))>0.05) or (ztm(!i,1)=1 and
zaim(!i,1)=0 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(5+(14*(!i-1)),7))>0.05) or (ztm(!i,1)=1 and zaim(!i,1)=1 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(6+(14*(!i-
1)),6))>0.05) or (ztm(!i,1)=1 and zaim(!i,1)=1 and @val(y_f!fmod_{%s}_om(7+(14*(!i-
1)),2))<0.05 and @val(y_f!fmod_{%s}_om(6+(14*(!i-1)),7))>0.05) or (_a1>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_a1+(14*(!i-
1)),6))>0.05) or (_a1>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_a1+(14*(!i-1)),7))>0.05) or (_a2>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_a2+(14*(!i-
1)),6))>0.05) or (_a2>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_a2+(14*(!i-1)),7))>0.05) or (za2(!i,1)>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_a2row+(14*(!i-
1)),6))>0.05) or (za2(!i,1)>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_a2row+(14*(!i-1)),7))>0.05) or (zgch(!i,1)>6 and
@val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))>0.05 and @val(y_f!fmod_{%s}_om(_grow+(14*(!i-
1)),6))>0.05) or (zgch(!i,1)>6 and @val(y_f!fmod_{%s}_om(7+(14*(!i-1)),2))<0.05 and
@val(y_f!fmod_{%s}_om(_grow+(14*(!i-1)),7))>0.05) then
'...when conditionkeep is true - keep initial SBC (do nothing)
        else
'when condition is false (current SBC lower)...
'update infs, eqn, cv and r2,
'replace eqn for keeping with one for current lower sic model
        infs = @val(y_f!fmod_{%s}_om((6+((!i-1)*14)), 2))
        d y_F!feq_{%s}_om_s
        copy eq_F!f_M!i y_F!feq_{%s}_om_s
        copy cv_f!f_M!i_{%s}_om y_F!fcv_{%s}_om_s
'       copy r2_F!f_M!i_{%s}_om y_F!fr2_{%s}_om_s
'overwite bestout for this model with lower SBC model
        for !r = 1 to 13
        for !c = 1 to 11
        y_asmin_{%s}_om(!r+(((!f-1)*28)+14),!c) = y_f!fmod_{%s}_om((!r+((!i-1)*14)),!c)
        next
        next
        endif
        next
'insert comment labelling output copied to y_asmin_{%s}_om
        y_asmin_{%s}_om(5+((!f-1)*28),1) = "AIC *MIN*"
        y_asmin_{%s}_om(6+(((!f-1)*28)+14),1) = "SBC *MIN*"
'comparing standard error of min aic and min sic models
'note se of each model, aic and sic
        scalar _se_a_{%s}_om = @val(y_asmin_{%s}_om(3+((!f-1)*28),2))
        scalar _se_s_{%s}_om = @val(y_asmin_{%s}_om(17+((!f-1)*28),2))
'IF AIC MODEL HAS LOWER SE (difference will be negative)...
        if _se_a_{%s}_om < _se_s_{%s}_om then
'copy aic model only from asmin table to y_bestmod table
```

```
        for !r = 1 to 13
        for !c = 1 to 11
        y_bestmod_{%s}_om(!r+((!f-1)*14),!c) = y_asmin_{%s}_om(!r+((!f-1)*28),!c)
        next
        next
'delete old versions, rename aic cv, r2, eq (drop "_a"), and delete sic versions
        copy y_F!feq_{%s}_om_a y_F!feq_{%s}_om
        copy y_F!fcv_{%s}_om_a y_F!fcv_{%s}_om
'       copy y_F!fr2_{%s}_om_a y_F!fr2_{%s}_om
        d y_F!feq_{%s}_om_a
        d y_F!fcv_{%s}_om_a
'       d y_F!fr2_{%s}_om_a
        d y_F!feq_{%s}_om_s
        d y_F!fcv_{%s}_om_s
'       d y_F!fr2_{%s}_om_s
        else
'otherwise do nothing and continue to the next if condition...
        endif
'IF SBC MODEL HAS LOWER SE (difference will be positive)...
        if _se_a_{%s}_om > _se_s_{%s}_om then
'copy sic model only from asmin table to y_bestmod table
        for !r = 1 to 13
        for !c = 1 to 11
        y_bestmod_{%s}_om(!r+((!f-1)*14),!c) = y_asmin_{%s}_om(!r+14+((!f-1)*28),!c)
        next
        next
'delete old versions, rename aic cv, r2, eq (drop "_a"), and delete sic versions
        copy y_F!feq_{%s}_om_s y_F!feq_{%s}_om
        copy y_F!fcv_{%s}_om_s y_F!fcv_{%s}_om
'       copy y_F!fr2_{%s}_om_s y_F!fr2_{%s}_om
        d y_F!feq_{%s}_om_a
        d y_F!fcv_{%s}_om_a
'       d y_F!fr2_{%s}_om_a
        d y_F!feq_{%s}_om_s
        d y_F!fcv_{%s}_om_s
'       d y_F!fr2_{%s}_om_s
        else
'otherwise do nothing and continue to the next if condition...
        endif
'IF SES ARE EQUAL (I.E. IF MIN AIC AND SBC MODELS ARE THE SAME)
        if _se_a_{%s}_om = _se_s_{%s}_om then
'copy sic model only from asmin table to y_bestmod table
        for !r = 1 to 13
        for !c = 1 to 11
        y_bestmod_{%s}_om(!r+((!f-1)*14),!c) = y_asmin_{%s}_om(!r+14+((!f-1)*28),!c)
        next
        next
'delete old versions, rename aic cv, r2, eq (drop "_a"), and delete sic versions
        copy y_F!feq_{%s}_om_s y_F!feq_{%s}_om
        copy y_F!fcv_{%s}_om_s y_F!fcv_{%s}_om
'       copy y_F!fr2_{%s}_om_s y_F!fr2_{%s}_om
        d y_F!feq_{%s}_om_a
        d y_F!fcv_{%s}_om_a
'       d y_F!fr2_{%s}_om_a
        d y_F!feq_{%s}_om_s
        d y_F!fcv_{%s}_om_s
'       d y_F!fr2_{%s}_om_s
```

```
'note that both aic and sic have selected the same model
        y_agree_{%s}_om(!f,1) = 1
        else
'otherwise do nothing and continue to the next if condition...
        endif
        endsub

        subroutine peercvs
        smpl @all
'called after all series are calculated, so loop through each smplspec
        for %s x4 x8 x12 ind all
'forming series of mean cv of peers for each sri fund
'there are 16 sri funds, fund start and end #s listed in table zsri_ranges
'loop below is one for each sri fund; must convert number of funds
'analsysed (!fundmax) into number of these that are sri (_srisum)
        scalar _srisum = 0
        scalar _divisor_all = 0
        for !k = 1 to !fundmax
        _srisum = _srisum + @val(zsri_funds(!k,1))
        next
'need this below...
        series _cvsum_all = 0
'now... for each sri fund...
        for !sri = 1 to _srisum
        scalar _divisor_byfund = 0
        series _cvsum_byfund = 0
        scalar _srifund = @val(zsri_ranges(!sri,1))
        scalar _peerstart = _srifund+1
        scalar _peerend = @val(zsri_ranges(!sri,2))
'also need scalar _srifund as string to name relevant series
        %str = @str(_srifund)
'now... for each peer within an sri fund...
        for !i = _peerstart to _peerend
'if fund not included in sample (zfundsin = 0), don't add to cumulating sum
        if zfundsin_{%s}(!i,1) = 0 then
'do nothing - don't add anything to the cumulating sum
        else
'if fund is included, add its cv series to cumulating sum
        _cvsum_byfund = _cvsum_byfund + y_f!icv_{%s}_om
        endif
'no of series included = sum of relevant zfundsin table rows
        _divisor_byfund = _divisor_byfund + @val(zfundsin_{%s}(!i,1))
        next
'... and divide sum by number of series to get mean cv of peers by fund
        series y_f{%str}cvpr_{%s}_om = _cvsum_byfund/_divisor_byfund
'also cumulate each _cvsum_byfund series to get overall sum, then mean
        _cvsum_all = _cvsum_all + _cvsum_byfund
'this is repeated for each value of !sri
'i.e. for each sri fund listed in table zsri_ranges
        next
'calculate _divisor_all as sum of funds inluded minus # of sris
        for !h = 1 to !fundmax
        _divisor_all = _divisor_all + @val(zfundsin_{%s}(!h,1))
        next
        _divisor_all = _divisor_all - _srisum
'so mean cv across all peers is
        series y_cvprfy_{%s}_om = _cvsum_all/_divisor_all
```

```
'now want to sum cv across all sri funds...
        series _cvsrisum_{%s}_om = 0
        for !sri = 1 to _srisum
'get number of sri fund to add from table zsri_ranges
        %str2 = @str(zsri_ranges(!sri,1))
'and add each sri fund's cv to the cumulative sum...
        _cvsrisum_{%s}_om = _cvsrisum_{%s}_om  + y_f{%str2}cv_{%s}_om
        next
'divide by _srisum (# of sri funds analysed) to get average over all sris
        series y_cvsrify_{%s}_om = _cvsrisum_{%s}_om /_srisum
'above includes "sri" Framlington f15; "fy" is for "Framlington yes"
'want to repeat excluding f15, fn = Framlington no
        series y_cvsrifn_{%s}_om = (_cvsrisum_{%s}_om - y_f15cv_{%s}_om) /(_srisum-1)
'similarly, peer mean above includes Framlington, want without
        if %s = "ind" or %s = "x4" or %s = "x8" or %s = "x12" then
'remove three funds 16, 18 and 19 from peer mean
        series y_cvprfn_{%s}_om = (_cvsum_all - y_f16cv_{%s}_om - y_f18cv_{%s}_om -
y_f19cv_{%s}_om)/(_divisor_all - 3)
        endif
        if %s = "all" then
'remove four funds 16, 17, 18 and 19 from peer mean
        series y_cvprfn_{%s}_om = (_cvsum_all - y_f16cv_{%s}_om - y_f17cv_{%s}_om -
y_f18cv_{%s}_om - y_f19cv_{%s}_om)/(_divisor_all - 4)
        endif
'end of smplspec loop (entire subroutine)
        next
        endsub

        subroutine standerrs
        for %s x4 x8 x12 ind all
'puts se for each selected model in a table, one table for each sample spec
        for !i = 1 to 169
        scalar _se_{%s}_om = @val(y_bestmod_{%s}_om(3+14*(!i-1),2))
        y_stand_errs_{%s}_om(!i, 1) = _se_{%s}_om
        next
        next
        endsub

        subroutine indsample
'varies sample from sri fund to sri fund for smplspec ind
'sample s2
        if %s = "ind" and !f>=1 and !f<=5 then
        smpl 1987:02 2004:07
        endif
'sample s4
        if %s = "ind" and !f>=15 and !f<=19 then
        smpl 1987:05 2004:07
        endif
'sample s5
        if %s = "ind" and !f>=20 and !f<=30 then
        smpl 1987:11 2004:07
        endif
'sample s7
        if %s = "ind" and !f>=39 and !f<=52 then
        smpl 1988:03 2004:07
        endif
'sample s6
```

```
        if %s = "ind" and !f>=31 and !f<=38 then
        smpl 1989:03 2004:07
        endif
'sample s8
        if %s = "ind" and !f>=53 and !f<=58 then
        smpl 1989:05 2004:07
        endif
'sample s9
        if %s = "ind" and !f>=59 and !f<=63 then
        smpl 1989:05 2004:07
        endif
'sample s11
        if %s = "ind" and !f>=80 and !f<=99 then
        smpl 1989:07 2004:07
        endif
'sample s10
        if %s = "ind" and !f>=64 and !f<=79 then
        smpl 1990:03 2004:07
        endif
'sample s12
        if %s = "ind" and !f>=100 and !f<=110 then
        smpl 1990:03 2004:07
        endif
'sample s13
        if %s = "ind" and !f>=111 and !f<=122 then
        smpl 1990:06 2004:07
        endif
'sample s14
        if %s = "ind" and !f>=123 and !f<=127 then
        smpl 1991:08 2004:07
        endif
'sample s3
        if %s = "ind" and !f>=6 and !f<=14 then
        smpl 1993:09 2004:07
        endif
'sample s15
        if %s = "ind" and !f>=128 and !f<=132 then
        smpl 1992:07 2002:06
        endif
'sample s16
        if %s = "ind" and !f>=133 and !f<=141 then
        smpl 1994:11 2004:07
        endif
'sample s17
        if %s = "ind" and !f>=142 and !f<=153 then
        smpl 1995:03 2004:07
        endif
'sample s18
        if %s = "ind" and !f>=154 and !f<=165 then
        smpl 1995:08 2004:07
        endif
        endsub

        subroutine analysis
'introduce %bm string variable for benchmarks
'relevant %bm is held in table zbench_o
        %bm = zbench_o(!f,1)
```

```
'each benchmark also has its timing dummy variable
        %bm_tm = zbench_o(!f,1) + "_tm"
'OLS models 1 to 3 are not in the main arch loop
        for !m = 1 to 3
'set top line of output table and double line section end
        scalar top = 1 + 14*(!m-1)
        setline(y_f!fmod_{%s}_om,top+13)
'form model label string
        %modlabel = zmodel_om(!m,2)
'form model number string
        %m = @str(!m)
'insert this info in output table
        y_f!fmod_{%s}_om(top,2) = %modlabel
        y_f!fmod_{%s}_om(top+1,2) = "M" + %m
'also to ensure series resid is correctly updated
        resid = na
'estimate robust model and freeze
        %modspec = zmodel_om(!m,4)
        equation eq_F!f_M!m.{%modspec}
        freeze(rob_tab1) eq_F!f_M!m.results
'estimate usual model and freeze
        %modspec = zmodel_om(!m,3)
        equation eq_F!f_M!m.{%modspec}
        freeze(tab1) eq_F!f_M!m.results
'output subroutine (but no recursive graphs this time)
        call out_ls
        next
'*************************************************
'now begin main loop here for garch models starting at model 4
'note will run for any model #s (handy to see which crash)
'but must run from 4 contiguously to get correct output !!!
'last model currently #201
        for !m = 4 to !modelmax
'set top line of output table and double line section end
        scalar top = 1 + 14*(!m-1)
        setline(y_f!fmod_{%s}_om,top+13)
'form model label string
        %modlabel = zmodel_om(!m,2)
'form model number string
        %m = @str(!m)
'insert this info in output table
        y_f!fmod_{%s}_om(top,2) = %modlabel
        y_f!fmod_{%s}_om(top+1,2) = "M" + %m
'also to ensure series resid is correctly updated
        resid = na
'know that some models crash with some funds
'this info (fund #) in 6th and subsequent columns of zmodel_om
'i.e. zmodel_om row = !m, column = (!f+5) either zero (run) or !f (skip)
        %skip = zmodel_om(!m,!f+5)
        if @val(%skip) <> !f then
'i.e. continue if current model # isn't listed else modelskip
'(can amend this to search multiple columns if needed)
'check error count before estimating model
        !errs_pre = @errorcount
'estimate robust model first
        %modspec = zmodel_om(!m,4)
        equation eq_F!f_M!m.{%modspec}
```

```
'check error after estimating model
        !errs_post = @errorcount
'has there been an error?
        if !errs_post = !errs_pre then
'if no error, continue with estimation & output, else - modelskip
'freeze estimation results
        freeze(rob_tab1) eq_F!f_M!m.results
'estimate usual model and freeze
        %modspec = zmodel_om(!m,3)
        equation eq_F!f_M!m.{%modspec}
        freeze(tab1) eq_F!f_M!m.results
'produce cv and r2 for every eqn (delete later after picking low aic sic)
'can produce lots of errors, so check for errors...
        !errs_pre = @errorcount
        eq_F!f_M!m.makegarch cv_f!f_M!m_{%s}_om
        eq_F!f_M!m.makeresids res_f!f_m!m_{%s}_om
        !errs_post = @errorcount
'...and if no error continue... else modelskip (at end of subroutine)
        if !errs_post = !errs_pre then
'output subroutine
        call out_arch
'       call infcriteria
'if estimation error found above, skip to here
        else
        call modelskip
        endif
        else
        call modelskip
        endif
        else
        call modelskip
        endif
        next
        endsub
'=================================
'MAIN PROGRAM FROM HERE -
'SUBROUTINES ABOVE
'=================================
'state max fund number (up to 169 incl fce & peers or 165 without) and model number (up to
201)
        !fundmax = 165
        !modelmax = 201
'set timer
        tic
'get rid of output from previous runs
        d y* eq* g* r* _*
'from here loops through three sample specs
        for %s x4 x8 x12 ind all
        if %s = "all" then
        smpl @all
        endif
        if %s = "ind" then
'do nothing here; smpl changes with fund #, must be in !f loop below
        endif
        if %s = "x4" then
        smpl 1988:04 2004:07
        endif
```

```
        if %s = "x8" then
        smpl 1989:07 2004:07
        endif
        if %s = "x12" then
        smpl 1991:08 2004:07
        endif
'make a table for best info criteria models
        call make_bestout_table
'loop through funds up to maximum set above
'### (SET START FUND HERE, NORMALLY = 1)
        for !f = 1 to !fundmax
'if smplspec = ind, call subroutine to make sample change with fund #
        if %s = "ind" then
        call indsample
        endif
'otherwise sample is as set above for all, x4, etc.
'check that current fund is wanted, i.e. =1 in relevant table zfundsin
        if zfundsin_{%s}(!f,1) = 1 then
'make a table for output for each fund
        call make_output_table
'and insert regressions
        call analysis
'search output for best info criteria and insert in bestout
        call infcriteria
        d eq* i* t* r2_* res_*
        d cv_*
        else
'else, if fund not =1 in zfundsin, skip to here (do nothing) and next fund...
        endif
'end of !f loop through funds for a given smplspec
        next
'end of smplspec loop
        next
'calculate mean cv of peers etc
        call peercvs
'note se of regression for selected models, list in table y_stand_errs_om
        call standerrs
        d _*
'display elapsed time in seconds in status line
        toc
'and save as scalar
        scalar time_elapsed_mins = @toc/60
        scalar time_elapsed_hrs = @toc/(60*60)
```

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The Financial Performance of a Socially Responsible Investment Over Time and a Possible Link with Corporate Social Responsibility

Greig A. Mill

ABSTRACT. This paper empirically examines the financial performance of a UK unit trust that was initially "conventional" and later adopted socially responsible investment (SRI) principles (ethical investment principles). Comparison is made with three similar conventional funds whose investment objectives remained unchanged. Analysis techniques employed in previous studies find similar results: mean risk-adjusted performance is unchanged by the switch to SRI, with no evidence of over-or under-performance relative to the benchmark market index by any of the four funds. More interestingly, changes in variability of returns over time are also modelled using generalised autoregressive conditional heteroscedasticity models, not previously applied to SRI funds so far as is known. Results show a temporary increase in variability of returns, followed by a return to previous levels after around 4 years. Evidence shows the increased variability to be associated with the adoption of SRI rather than with a change in fund management. Possible explanations for the subsequent reduction in variability include the spread of corporate social responsibility activities by firms and learning by fund managers. In addition to reporting on a previously unobserved phenomenon, this paper raises questions for further research.

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KEY WORDS: corporate social performance, corporate social responsibility, ethical investment, learning by doing, mutual funds, socially responsible investment

ABBREVIATIONS: CFP, corporate financial performance; CSP, corporate social performance; CSR, corporate social responsibility; GARCH, generalised autoregressive conditional heteroscedasticity; OEIC, open-ended investment company; SRI, socially responsible investment

Introduction

Following a brief review of socially responsible investment (SRI) and of research into the financial performance of such investments, new evidence on the financial performance of a SRI fund is presented below. The fund is unusual in that it initially pursued conventional investment objectives and subsequently amended these to reflect typical SRI criteria. The evidence presented below is novel in that it demonstrates changes in the volatility of SRI performance over time. Volatility of returns increases for almost 4 years and then declines to previous levels. Two possible explanations for the increase in volatility are examined: the switch to SRI objectives, and a change in fund management. The evidence below favours the former explanation.

Somewhat more speculatively, two possible explanations for the decline in volatility to previous levels are considered. First, the increased adoption of corporate social responsibility (CSR) practices by firms. The effect, if any, of SRI activity on company or market behaviour – and investors' perception of this – is the subject of ongoing research (e.g., Cox et al., 2004; Haigh and Hazelton, 2004; Heinkel et al., 2001; Lewis and Mackenzie, 2000a,b; Michelson et al., 2004; O'Rourke, 2003; Rivoli, 2003; Schepers and Sethi, 2003; Sparkes and Cowton, 2004; Teoh et al., 1999). The intriguing possibility is raised below of an effect operating in the opposite direction – the spread of CSR activities may impact (beneficially) on the financial performance of SRIs by expanding the set of investment opportunities available. Second, learning by doing by fund mangers is also a possible explanation and is briefly discussed.

Socially responsible investment is a growing international phenomenon. Within Europe, in addition to Sweden (where the first SRI retail fund was established in 1965) and the UK (the largest European SRI market) SRI funds now operate in Belgium, France, Germany, Norway, Switzerland, the Netherlands, Austria, Finland, France, Spain and Italy (Kreander, 2001). Total European SRI assets in 2002 were estimated at £19.8 billion with well over 200 SRI funds. US SRI assets totalled around $2,332 billion in 2001. Estimates of total Australian SRI assets range from A$2 billion to A$10.5 billion. Canada has around 50 SRI funds and Japan is rapidly developing a distinctive form of SRI (Sparkes, 2002).

Most of the above SRI activities are relatively recent, however, with longer-established SRI funds commonest in the US and UK. Broadly similar accounts of the recent "astounding escalation" in SRI can be found, for example, in Waring and Lewer (2004) and Schueth (2003).

"SRI" has tended to replace the older term "ethical investment", although they are arguably not exact synonyms. While meaningful distinctions are at times made between these (see, e.g., Sparkes and Cowton, 2004; Sparkes 2002) both terms refer to:

> ...the exercise of ethical and social criteria in the selection and management of investment portfolios, generally consisting of company shares (stocks). (Cowton, 1994)

Cowton continues:

> This contrasts with the standard depictions of investment decisions, which concentrate solely on financial return... Ethical investors care not only about the size of their prospective financial return and the risk attached to it, but also its source – the nature of the company's goods and services, the location of its business or the manner in which it conducts its affairs.

The question of whether such additional considerations impact on financial return follows naturally from this definition.

For many investors SRI involves the selection of holdings of company shares from a subset of publicly listed companies that are seen as meeting "socially responsible" criteria. Thus SRI and CSR are often portrayed as closely related phenomena, for example:

> ...corporate social responsibility (CSR) and socially responsible investing are in essence mirror images of each other. Each concept basically asserts that business should generate wealth for society but within certain social and environmental frameworks. CSR looks at this from the viewpoint of companies, SRI from the viewpoint of investors in those companies (Sparkes, 2002).

This broad conceptual similarity may be reflected in linkages in the behaviour of the two phenomena. For example, the financial performance of SRIs seems at times to be assumed to depend in a simple way on the relationship between corporate social performance (CSP) and corporate financial performance (CFP) at the scale of the individual firm.

The relationship between the CSP of a firm and the financial performance of that firm has been much researched, with over a dozen reviews of numerous empirical studies published. See, for example, Wood and Jones (1995) – reviewing 60 empirical studies from 1970 to 1994; Pava and Krausz (1996) – 21 studies from 1972 to 1992; Margolis and Walsh (2001) – 95 studies from 1972 to 2000; Margolis and Walsh (2003) – 127 studies from 1972 to 2002; Orlitzky et al. (2003) – 52 studies from 1972 to 1997; and Salzmann et al. (2005) – 15 studies from 1975 to 2001.

One review concludes that: "...there is a positive association, and certainly very little evidence of a negative association, between a company's social performance and its financial performance" (Margolis and Walsh, 2003), and another: "...across studies, CSP [corporate social performance] is positively correlated with CFP [corporate financial performance]..." (Orlitzky et al., 2003).

However, if it is true that there is a positive association between the social and financial performance *of individual firms* it does not follow from this that SRIs consisting of portfolios of shares of such firms should be expected to provide a superior financial return relative to similar conventional investment portfolios, or indeed that the financial return should necessarily differ at all, other than by chance.

A non-SRI investment fund is free to hold shares in any company, including socially responsible companies, while a SRI fund focuses on companies deemed socially responsible. Other things equal, only if the conventional investment fund is for some reason less aware of the good qualities of socially responsible companies (as suggested by the above studies) might the SRI fund be expected to perform better. Conventional investment funds have the same opportunity as SRI funds to benefit from any good financial performance of socially responsible companies. On the other hand, a change over time in the number of socially responsible firms relative to conventional firms might produce an effect on SRI performance, since this directly affects a SRI fund's available investment opportunities relative to those of a conventional fund. Note the caveat "other things equal"; for a fuller discussion of sources of differences in performance between SRI and conventional investment funds, see Mill and Holland (2005).

Most individual SRI investors utilize mutual funds in North America, and unit trusts or open-ended investment companies (OEICs) in Europe. Some institutions with significant assets manage their own SRI portfolios, for example, the Methodist Church and the Society of Friends (Quakers) in the UK and The Norwegian Government Petroleum Fund which adopted SRI principles in November 2004 making it possibly the largest SRI fund anywhere (Norwegian Ministry of Finance, 2005).

The recent expansion of SRI activity in the UK, Germany and Australia has arisen largely due to the adoption of SRI by large institutional investors such as pension funds and insurance companies, encouraged by regulatory change. In the UK, amendments to section 35(3)(f) of the 1995 Pensions Act came into force in July 2001, requiring all occupational pension funds to state "the extent (if at all) to which social, environmental or ethical considerations are taken into account in the selection, retention and realisation of investments..." (HMSO, 1999). The UK pension fund market (£800 billion in 2000) is vast in comparison with the SRI retail fund market (£3.3 billion).

SRI principles have been adopted by the BT Pension Scheme (£29 billion) and the Universities Superannuation Scheme (£22 billion). A survey of the 500 largest UK pension funds and 97 local authority pension funds found that 59% of respondents, representing 78% of assets, were intending to adopt SRI principles (Green, 2001). A more recent survey of pension fund trustees found that 69% had a statement of investment principles featuring SRI issues, and a majority felt that social, environmental and employment practices, and good corporate governance generally, impacted on market value, particularly in the longer term (Gribben and Olsen, 2003; see also Gribben and Faruk, 2004).

Some SRI performance research has examined published market indices such as the US Domini 400 Social Index (e.g., much of Camejo, 2002; Sauer, 1997) or specially produced indices (Havemann and Webster, 1999).

Many US studies examine the performance of specially constructed SRI and non-SRI portfolios (Bibartolomeo and Kurtz, 1996; Butz and Plattner, 2000; Diltz, 1995; Guerard, 1997; Stone et al., 2001) rather than how actual SRI funds into which individuals may invest ("retail" funds) have fared. The use of specially constructed portfolios makes it possible to control for performance effects due not to "social responsibility" or "ethicalness" as such but to "coincidental" concentration in investment sectors (say, smaller companies or IT and communications) that are doing well or badly over a given period of time. The aim is to identify a distinct SRI effect if this exists. On the other hand, individual 'retail' investors in a mutual fund or unit trust/OEIC experience the overall net effect of SRI, along with any accompanying small company effects or investment sector effects.

The performance of actual retail SRI funds as opposed to portfolios constructed by researchers has been most studied in the UK and other European countries. The first such study appears to be Luther et al. (1992), followed by Luther and Matatko (1994). Mallin et al. (1995) introduced the "matched pair" approach referred to below, while Gregory et al. (1997) use a cross-sectional regression technique in addition to pairwise comparisons of SRI and non-SRI funds. Kreander et al. (2002) considerably develop Mallin et al.'s "matched pair" approach in terms of model used and statistical approach and expand consideration to seven European countries. Plantinga and Scholtens (2001) consider a small number of funds from three European countries, while Bauer et al. (2002) analyse 103 SRI funds from Germany, the UK and USA. Hamilton et al. (1993), Geczy et al. (2003) and Statman (2000) consider the performance of US SRI funds, while Bauer et al. (2003a) do likewise for Canada and Cummings (2000) and Bauer et al. (2003b) for Australia.

The broad picture to emerge from these SRI studies (subject to various caveats regarding benchmarks, risk factors, choice of funds for analysis and comparison, etc.), is that there is little evidence of SRI funds over- or under-performing relative to the market, and also little evidence of a difference between the SRI and non-SRI groups. SRI funds appear on the whole to follow the market similarly to their non-SRI counterparts, each group generally failing to "beat the market" but also not generally underperforming relative to the market.

The above studies of actual SRI funds have two features in common. First, throughout the time period under consideration, a given fund or portfolio is always either "SRI" or "non-SRI" and in this sense the comparisons made are *cross-sectional*. Almost all funds are initially launched either with or without SRI objectives (most without), and this rarely changes. Second, although the variability of returns in relation to the market is generally taken into account in as much as "risk-adjusted" performance measures are used, attention has been firmly focussed on the *mean level* of returns over time.

The research presented below differs with regard to both of these features. First, Family Charities Ethical (FCE), a UK unit trust, was initially launched with conventional investment objectives and subsequently "became SRI". This provides an unusual opportunity to make a *time-series* comparison of conventional and SRI performance. Second, in what follows investigation of the mean level of returns pre- and post-SRI is undertaken in a similar manner to previous studies. But explicit modelling of the *variability* of returns about this mean – little considered in previous studies – proves to be of greater interest.

The remainder of this paper proceeds as follows. The next section, "Data," introduces the SRI fund of interest, along with similar non-SRI funds ("controls") for comparison. The subsequent section, "Modelling Mean Returns," undertakes analysis of mean returns in a similar manner to previous studies. This is followed by "Modelling of Variability of Returns," where use is made of variance modelling techniques common in the financial economics literature but not previously applied to SRI funds, so far as is known. Evidence is presented of a temporary increase in variability of returns coincident with the adoption of SRI objectives, that is not found in similar non-SRI funds. Then "SRI Effect or Management Change Effect?" examines the alternative explanation that the increased volatility is due to changes in the management of the fund, finding that this fits the data less well. The final section concludes with comments on the interpretation of the results, including brief discussion of possible causes for the return of volatility to previous levels, and possible directions for future research.

Data

Family Charities Ethical Trust (FCE) was launched in March 1982 as The Mencap Unit Trust, later changing name to United Charities Trust and then to FCE in 1997. A number of charities invest in the fund, and private investors can opt to covenant their investment income to one of these. The investment objective of FCE was initially "consistent long-term growth of both income and capital" (FCIM, 1993) from a portfolio that "may include a proportion of overseas investments". UK equities have typically

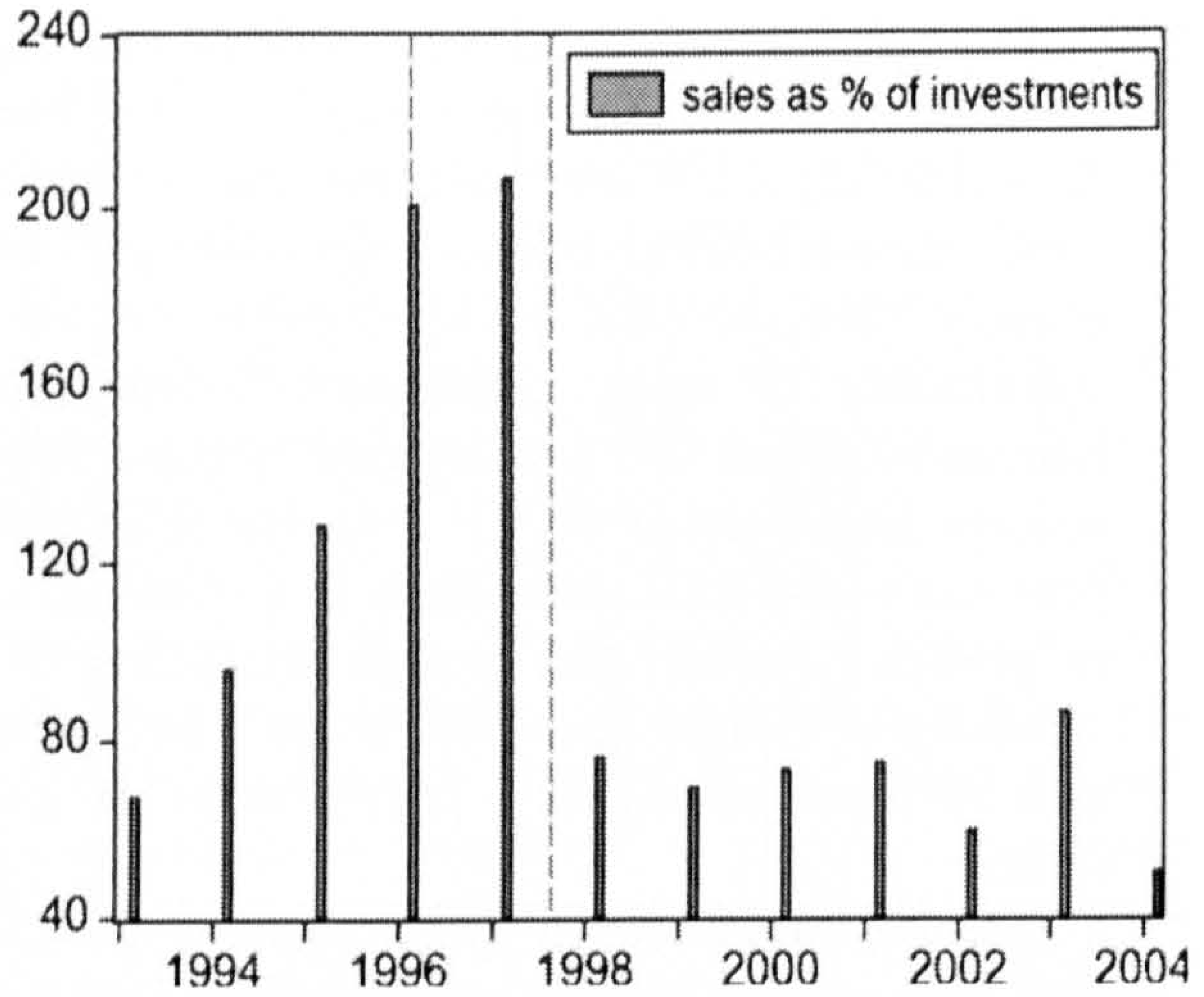

Figure 1. Annual proceeds from sales of investments as a percentage of investments at market value for fund FCE.

formed between 80% and 90% of FCE portfolio value.

In March 1996 a statement of SRI principles was added: "...whilst avoiding investments in companies which generate significant turnover from alcohol or tobacco or which manufacture weapons, supply ozone depleting chemicals, test cosmetics or toiletries on animals, or use significant quantities of tropical hardwood." Further additions followed in September 1996: "using intensive farming methods," "trade in prohibited pesticides," "activities which significantly pollute waterways" and "company groups who have registered companies in a significant number of countries identified as violating human rights." The statement on weapons manufacture was amended to "export of goods or military services for military users," and use of tropical hardwood was amended to "extracting or importing tropical hardwood." No changes in investment objectives have occurred since 1996.

The change to SRI does appear to have impacted on fund management practice. This can be seen by examining the proceeds from sales of investments (company shares) as a percentage of total investments in the 12 months to 31 March each year, shown in Figure 1.

In Figure 1 SRI adoption in March-96 is indicated by the first of two broken vertical lines (the second vertical line in September-97 relates to a change in fund management and is discussed below).

Figure 1 shows that in the two years to March-96 and March-97 (leading up to and just subsequent to the March-96 adoption of SRI principles) sales of investments were around twice the typical level for this fund (generally around 60–100% of portfolio value). That these increased sales represent a realignment rather than a reduction of portfolio holdings is indicated by the year-on-year increase in total (nominal) portfolio value between 1995 and 2000 resulting in a seven-fold increase overall.

In the year to March-96 sales of shares in 12 companies, amounting to 46.4% of total portfolio value, can be linked to criteria in the new SRI principles: McBride (6.1%, personal care products), Smiths Industries (5.8%, aerospace engineering), Morland (4.5%, brewer), Allied Domecq (4.3%, alcohol retailer), Kwik Save (4.1%, alcohol and tobacco retailer), ML Laboratories (3.6%, pharmaceutical development), T&N (3.6%, infamous asbestos processors), IMI (3.4%, alcohol dispensers), MacDonald Hotels (3.2%, alcohol retailers), Pliva DD (3.0%, pharmaceuticals and cosmetics), Victrex (2.6%, chemicals, aerospace), Greenalls (2.2%, brewer). It may be that individually some of these companies would have been sold for purely financial reasons, but it is notable that taken together they comprise around half of investment sales in a year in which total investment sales are around twice the typical level.

Major additions to FCE's portfolio in 1996 and 1997 included British Biotech (6.4% of portfolio value, biotechnology), Glaxo Wellcome (5.6%, pharmaceutical and healthcare), Platignum (5.2%, pen manufacturer), Abbey National (4.7%, banking), Cantab Pharmaceuticals (4.5%, vaccines and biotechnology), National Grid Group (4.2%, electricity transmission).

Information on changes in the composition of the control funds with which FCE is compared (see below) was not available. It is hoped that use of three control funds makes it unlikely that all three control funds underwent similar confounding portfolio changes over the relevant period of time.

Previous UK studies of SRI performance have adopted a "matched pair" approach whereby each SRI fund is matched with a single "similar" conventional fund. However, it is doubtful whether a single conventional fund can be accurately identified as the unique best standard of comparison for each SRI fund. And given that in the UK there are over

TABLE I

SRI fund Family Charities Ethical (shaded) and conventional "control" funds SUG, IUG and MCI

Fund	Label	Size (£m)	Launch	Data from/to
Family Charities Ethical	FCE	10.0	May-82	May-82/Mar-04
Solus UK Growth	SUG	8.9	Sep-81	May-82/Mar-04
ISIS UK Growth & Income	IUG	22.2	Jul-83	Dec-84/Mar-04
Martin Currie IF Income	MCI	28.5	Sep-83	Oct-83/Mar-04

2000 unit trusts and OEICs of which around 60 are SRI the "matched pair" approach seems unnecessarily restrictive.

Here comparable conventional funds ("controls") were initially selected as having the same benchmark (FTSE All-Share index), similar launch date (within 18 months either way of FCE) and similar fund size (money under management at the end of May 2001) using data from Reuters Hindsight financial database. Each fund is also listed under the same investment sector (UK All Companies) except for MCI (UK Equity Income). All but one of the potential control funds meeting the benchmark and launch date criteria are larger than FCE (£10m in May 2001), some many times larger since FCE is relatively small (in May 2001 the average unit trust size was £142m for UK unit trusts as a whole and £252m for unit trusts with FTSE All-Share index as benchmark). Three of the closest in size were selected: Solus UK Growth (SUG), ISIS UK Growth & Income (IUG) and Martin Currie IF Income (MCI) – see Table I.

The next closest matches with respect to fund size, not considered here, would be Friends Provident UK Focus (£36.8), since merged into ISIS UK Equity fund, followed by Abbey Assets & Earnings (£51.8m) and AEGON UK Tactical (£85.6m).

The control funds are "conventional" in the sense that their investment objectives are solely financial and make no mention of any "ethical" or "socially responsible" criteria (they are typically rather brief in comparison to FCE). For example, MCI has stated objective "to produce a rising income combined with capital growth through investment mainly in the United Kingdom... Investment will be in a mixture of ordinary shares, fixed interest and convertible stocks mainly in the UK" (Martin Currie Ltd., 2004). Similarly, IUG "focuses on achieving medium to long-term capital growth and a high level of income through investment primarily in UK equities" (ISIS 2004) while SUG aims for "long-term capital growth through a wide spread of primarily UK quoted securities" (Solus 2004).

The measure of fund performance used here is percentage change in nominal bid price from month end to month end with gross dividend income reinvested, from Reuters Hindsight financial database. Data runs from the launch of FCE in May 1982 (or from launch of the control, if later) until March 2004. This is a considerably longer time period than most previous studies of SRI performance.

Figure 2 shows monthly returns for FCE. Adoption of SRI objectives in March 1996 is shown by the shaded area to the right. Visual inspection alone reveals no immediately apparent trend or change in performance.

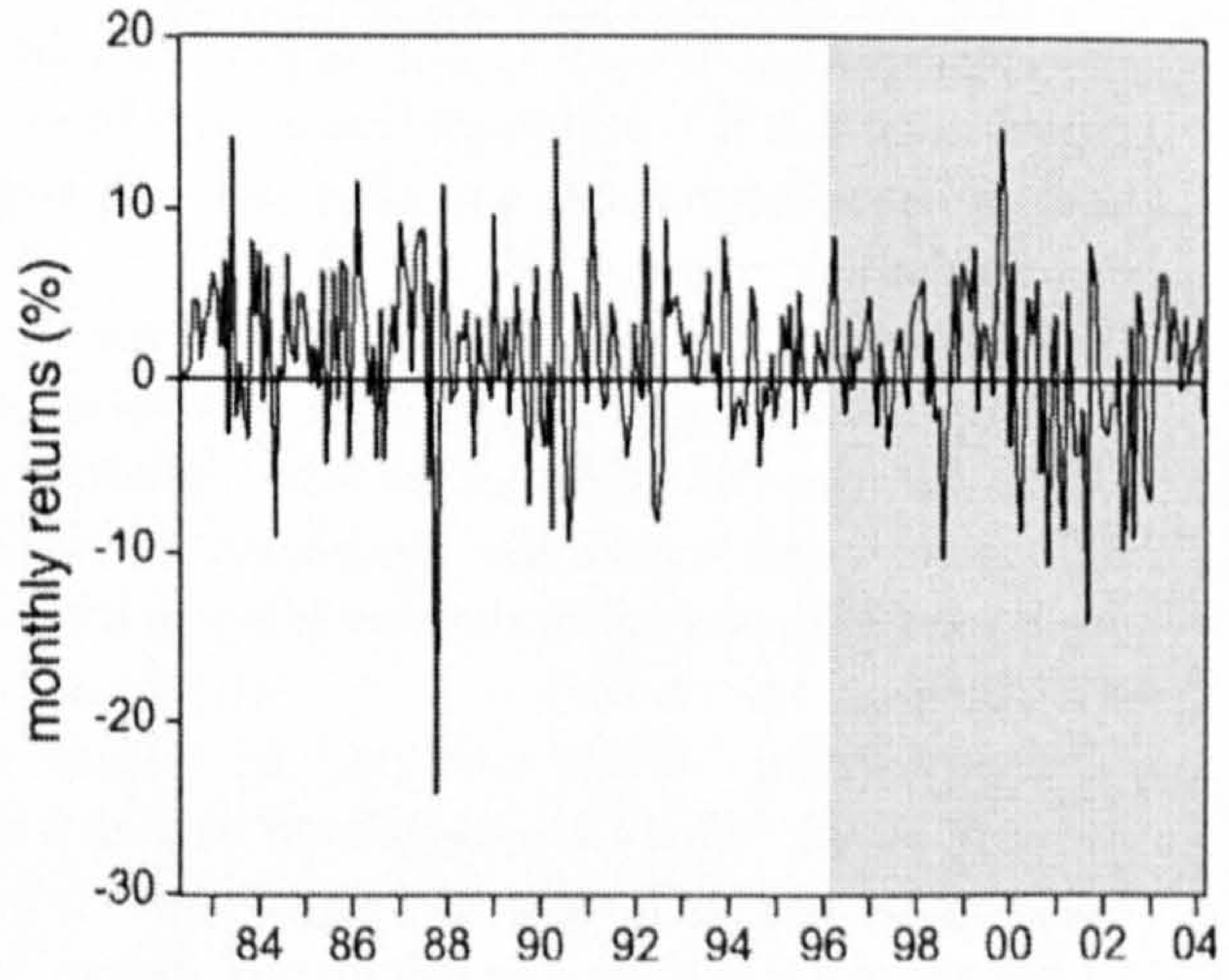

Figure 2. Monthly returns (%) for FCE.

TABLE II

Monthly returns: summary statistics for SRI fund FCE (shaded), FTSE all-share market index and controls SUG, IUG and MCI

	FTSE All	FCE	SUG	IUG	MCI
Mean					
Entire period	1.102	1.127	1.112	1.031	1.022
Pre-Mar-96[1]	1.375	1.374	1.617 *	1.230	1.291
Post-Mar-96[1]	0.618	0.688	0.216 *	0.678	0.544
Standard deviation					
Entire period	4.712	5.080	5.361	4.673	4.582
Pre-Mar-96[1]	5.069	5.058	5943 **	4.993 *	4.892 *
Post-Mar-96[1]	3.984	5.122	4.014 **	4.051 *	3.956 *

* Difference significant at 5% level; ** Difference significant at 1% level.
[1]Fund FCE adopts SRI principles in March 1996.

Table II shows mean and standard deviation of monthly returns for the four funds and for the Financial Times Stock Exchange All Share index (FTSE All) over each of three sample periods: pre-March-96 (pre-SRI for FCE), post-March-96 (post-SRI for FCE), and for the entire May 1982 to March 2004 period. This and all subsequent analysis was performed using Eviews 4.1 from Quantitative Micro Software.

In Table II the mean return to FCE compares well in each of the three periods considered with market index FTSE All and with the control funds. Mean returns in each case are much lower post-March-96 than pre-March-96. However, in only one case (SUG) is the difference in mean return from pre- to post-March-96 statistically significant at the conventional 5% level. This implies that in the other cases the fall in sample mean is within the bounds of random sample variation, which is large – see standard deviation.

When considering the variability of returns, FCE stands out as having greater standard deviation post-March-96 (this falls in the other cases) although the difference is not statistically significant. In contrast there is a significant fall in the variability of the three controls post-March-96.

In investment terms variability in returns is a measure of risk. There is a suggestion here that after adoption of SRI, FCE may be more "risky" relative to the control funds and/or the market index (since the standard deviation of these falls post-March-96 while FCE's does not). This is investigated further below.

Modelling mean returns

Each investment fund under consideration is a managed portfolio of shares (so that the terms "fund" and "portfolio" are somewhat interchangeable in this context). The mean and standard deviation data in Table II are unsatisfactory measures of portfolio performance since portfolio returns are earned from bearing and managing market risk. A model of equilibrium portfolio return in relation to market risk is required (Haugen, 2001).

Previous academic research on UK SRI fund performance makes use mainly of risk-adjusted portfolio performance measures derived from the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965a, b) and Mossin (1966), applied to performance assessment by Treynor (1965) and Jensen (1969). This is also true of many studies of conventional unit trusts (e.g., Leger, 1997; Blake and Timmermann, 1998).

In this approach performance assessment is based on estimation of the "ex post characteristic line":

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + \varepsilon_{pt} \qquad (1)$$

where r_{pt} is the return to the portfolio and r_{ft} is the return to a risk-free asset so that $r_{pt} - r_{ft}$ is the "excess return" to the portfolio in period t. The return to

UK Treasury Bills is used for r_{ft}. The return to the market as a whole is r_{mt} for which the FTSE All Share index is used (recall that all four funds list this as a benchmark). Final term ε_{pt} is a random error term.

Estimated coefficient α_p, the intercept of the characteristic line, is "Jensen's alpha" or simply "alpha": a measure of risk-adjusted portfolio performance, since theory suggests that in equilibrium this will be zero. Non-zero alpha α_p indicates "abnormal" returns, with positive α_p implying that active fund management has succeeded in "beating the market", whereas negative α_p indicates "underperformance" relative to the market index. The important caveat is that in sample data alpha estimates somewhat different from zero are to be expected by chance alone. Careful testing is needed to establish whether observed non-zero alpha estimates are statistically significant, that is, unlikely to be due to chance alone, and hence informative regarding portfolio performance.

β_p, 'beta', is the portfolio's normalised covariance with market movements. Beta is a measure of the extent to which portfolio/fund returns rise when the market index rises, and fall when the market index falls. In equilibrium a fund with beta somewhat less than 1 is expected to earn a mean return intermediate between the risk-free rate and that of the market index.

The possibility of a change from pre-March-96 to post-March-96 in either alpha or beta can be accommodated by introducing an SRI dummy variable D_t^S assigned the value of zero pre-March-96 and 1 thereafter:

$$r_{pt} - r_{ft} = a_p + a_p^S D_t^S + b_p(r_{mt} - r_{ft}) + b_p^S D_t^S (r_{mt} - r_{ft}) \tag{2}$$

Here estimated pre-SRI "alpha" is given by coefficient a_p and post-SRI alpha by $(a_p+a_p^S)$. Similar comments apply to "beta", b_p and $(b_p+b_p^S)$. Estimation of this characteristic line equation for FCE and the three control funds from May 1982 to March 2004 is shown in Table III.

Table III shows ordinary least squares (OLS) estimates for first alpha and then beta for characteristic line equations of SRI fund FCE and controls SUG, IUG and MCI.[1] Note that whereas pre-March-96 coefficients a_p and b_p estimate the pre-SRI alpha and beta, post-March-96 coefficients a_p^S and b_p^S estimate the post-SRI *change* in alpha and beta.

The alpha estimates are generally small in magnitude and none are significantly different from zero at conventional significance levels (i.e., $p > 0.05$). There is no evidence here of any over- or underperformance by FCE or the controls, nor of any change in performance post-March-96 that is distinguishable from random sample variation. Beta estimates are highly statistically significant, as expected, and are very similar in each time period. Again, there is no evidence of any change in performance post-SRI.

TABLE III

Alpha and beta estimates (OLS) for SRI fund FCE (shaded) and controls SUG, IUG and MCI

	FCE	SUG	IUG	MCI
Alpha				
Entire period alpha[1] (α_p)	0.1297	0.0479	−0.0443	−0.0158
Pre-Mar-96 alpha[2,3] (a_p)	0.0965	0.2495	−0.1031	0.0137
Post-Mar-96 change[2,3] (a_p^S)	0.0823	−0.5504	0.1464	−0.0823
Beta				
Entire period beta[1] (β_p)	0.9312 **	0.9117 **	0.9389 **	0.9253 **
Pre-Mar-96 beta[2,3] (b_p)	0.9387 **	0.9167 **	0.9314 **	0.9348 **
Post-Mar-96 change[2,3] (b_p^S)	−0.0221	−0.0282	0.0280	−0.0310

** significant at 1% level.
[1]See equation (1) in the text.
[2]Fund FCE adopts SRI principles in March 1996.
[3]See equation (2) in the text.

These results agree with previous research mentioned above that has generally found little evidence of difference (better or worse) between the financial performance of SRI funds and conventional funds. It appears that both pre- and post-SRI, FCE has in common with the controls an ability to match market performance, but not to exceed it.

However, Table III is concerned principally with the mean value of returns over time. Table II was suggestive of a difference between FCE and the control funds regarding the *variability* of returns.

Modelling variability of returns

The OLS method by which results in Table III were obtained assumes that the variance of error term ε_{pt} is unchanging over time. But "volatility clustering", whereby "large returns (of either sign)... follow large returns, and small returns (of either sign)... follow small returns" is frequently found in financial market data (Brooks, 2002). Where present, it can be modelled using autoregressive conditional heteroscedasticity (ARCH) models. ARCH was found to be present in FCE and the three controls using the standard statistical test (Engle, 1982), that is, the assumption of constant error variance is inappropriate.

The most commonly applied model of the ARCH type is the generalised autoregressive conditional heteroscedasticity GARCH(1,1) model of Bollerslev (1986) and Taylor (1986), of which Brooks (2002) says: "in general a GARCH(1,1) model will be sufficient to capture the volatility clustering in the data".[2] In addition to an equation describing the mean level of returns (e.g., the characteristic line equation above), an equation describing the variance of returns about this line is simultaneously estimated:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \delta\sigma_{t-1}^2 \qquad (3)$$

σ_t^2 is conditional variance: an estimate of variance about the mean equation at time t based on information up to time t, and ε_t^2 is the error term from the mean equation at time t. This is a GARCH(1,1) model, meaning that variance σ_t^2 is estimated using values of itself and of ε_t^2 one time-period prior to time t (one "lag" of each).

As with the characteristic line mean equation, an SRI dummy variable D_t^S can be included in the variance equation, giving:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_{\mathrm{SRI}} D_t^S + \delta\sigma_{t-1}^2 \qquad (4)$$

A significantly non-zero estimate for SRI dummy coefficient γ_{SRI} would indicate a step-change in conditional variance from March 1996, the time of FCE's adoption of SRI (i.e., in addition to any "volatility clustering" that may be present).

Table IV shows estimates over the entire data period from May 1982 to March 2004 for GARCH(1,1) models for FCE and controls SUG, IUG and MCI with varying SRI dummy variable γ_{SRI} specifications (none, step or pulse) as explained below.

The first "no dummy" row gives results for FCE with no SRI dummy in the variance equation. The mean equation results (alpha small and not significantly different from zero, beta of around 0.93 and highly statistically significant) agree closely with the OLS estimates in Table III. In the variance equation, both lagged error term γ_1 and lagged conditional variance term δ are statistically significant, confirming that a GARCH(1,1) model is appropriate.

In Table IV the next "step dummy" row of FCE results repeats GARCH(1,1) estimation but now includes an SRI dummy variable assigned a value of zero pre-March-96 and 1 thereafter, until the end of the data in March 2004. Again, mean equation results are similar, and variance equation results are statistically significant – most notably the large SRI dummy coefficient γ_{SRI} estimate of 3.911. The latter is now evidence of the post-SRI step increase in variability of FCE relative to the market index that was suggested by Table II.

The "step dummy" specification – zero pre-March-96 and 1 from March 1996 to March 2004 – arbitrarily imposes the condition that any post-SRI step change in variance is permanent (or persists until the end of the data). This need not be the case. A temporary increase in variance can be modelled using an SRI "pulse dummy" that is equal to 1 from March 1996 onwards for some specified number of months before returning to zero for the remainder of the data period.

A large number of pulse dummy durations are possible, each initially seemingly equally reasonable. Some means is required of selecting the pulse dummy duration that best fits the data. This was done using the Schwarz (1978) information criterion (SIC):

$$\mathrm{SIC} = -2(l/T) + k\log(T)/T \qquad (5)$$

where l is the value of the log of the likelihood function, k is the number of parameters estimated and T is the number of observations.[3]

SIC aims to provide a guide to model selection striking a balance between goodness of fit and parsimony in the number of explanatory variables (Enders, 2004). Models with smaller information criteria are preferable. For example, in the final column of Table IV the FCE "step dummy" model has lower SIC (4.6123) than the "no dummy" model (4.6185), confirming that inclusion of a SRI dummy variable improves the fit with the data, demonstrating that some post-SRI increase in variability is present.

GARCH(1,1) estimation was repeated for FCE with every possible SRI pulse dummy duration. The dummy duration giving the lowest SIC of 4.5206 was from SRI adoption in March 1996 until January 2000. Results are shown in the third "pulse dummy" row of FCE results in Table IV. The highly statistically significant SRI dummy coefficient of 0.3468 is evidence of a temporary increase in the post-SRI variance of FCE returns for the duration of the pulse dummy. Reassuringly, in addition to having a low SIC, this model has other good properties such as statistically significant coefficient estimates, so it can be concluded that the increase in FCE's variance is temporary rather than permanent.

This temporary increase in FCE's variance for just under 4 years following SRI adoption is distinct from the effect of volatility clustering (which is captured by the other GARCH components) and distinct from random sample variation (since the dummy variable is statistically significant). Thus it may be due to FCE's adoption of SRI. It is also possible that a sectoral or market-wide effect by coincidence occurs around the time that FCE adopts SRI. If so, one might expect to find evidence of this in the returns of the three control funds.

The remainder of Table IV shows GARCH(1,1) estimates for controls SUG, IUG and MCI first without SRI dummy, and then with the same SRI pulse dummy (March 1996 to January 2000) that was found to best fit FCE. Again, mean equation estimates are very similar to those in Table III, and the variance equations include highly statistically significant coefficients, confirming that volatility clustering is present.

In the case of conventional controls SUG and IUG, the other variance equation coefficient estimates are notably unchanged with or without inclusion of SRI variance pulse dummy variable γ_{SRI} and the pulse dummy coefficient itself is small and not statistically significant. That the appropriate model omits the pulse dummy is confirmed by SIC, which is lower for the model with no dummy (whereas in the case of FCE the pulse dummy model has the lowest SIC). Thus there is no evidence of any temporary increase in the volatility of these two controls over the period during which this is observed for FCE.

In the case of conventional control MCI the results are less striking but point to the same conclusion. Both the "no dummy" and "pulse dummy" models have statistically significant coefficients, and in particular the SRI dummy coefficient γ_{SRI} in the pulse dummy model is large and highly statistically significant. There is evidence here of a temporary sharp fall in the volatility of MCI's returns over the same period as the post-SRI increase in the volatility of FCE. However, the SIC is lower for the "no dummy" model so that on balance the data is better described in terms of an ongoing ARCH process.

Overall, examination of the three controls indicates that whatever caused the post-SRI increase in FCE variance seems not to have been a sectoral or market-wide effect, since the controls are not similarly affected.

The main results from Table IV are illustrated in Figures 3– 6 showing estimated conditional standard deviation (% per month) for FCE and controls SUG, IUG and MCI. These figures illustrate the variance equations from the FCE "pulse dummy" model and the control "no dummy" models summarised in Table IV.

TABLE IV

GARCH(1,1) estimates for SRI fund FCE (shaded) and controls SUG, IUG and MCI

	Mean equation[1]		Variance equation[2]				SIC[3]
	Alpha α_p	Beta β_p	γ_0	γ_1	δ	SRI dummy γ_{SRI}	
FCE							
No dummy	0.0807	0.9285*	0.2016	0.0735**	0.8886***	–	4.6185
Step	0.0561	0.9221***	3.3044***	0.2531***	−0.0544	3.9110**	4.6123
Pulse	0.0820	0.9445***	0.0585*	−0.0420**	1.0235***	0.3468***	4.5206
SUG							
No dummy	−0.0119	0.9088***	−0.0687***	−0.0045***	1.0080 ***	–	4.8455
Pulse	−0.0255	0.9073***	−0.0615**	−0.0052	1.0084***	−0.0252	4.8664
IUG							
No dummy	−0.0169	0.9401***	0.0040	−0.0201	1.0117***	–	3.4752
Pulse	0.0060	0.9452***	0.0009	−0.0213*	1.0138*	0.0043	3.4941
MCI							
No dummy	−0.0713	0.9283***	0.0545	0.0696*	0.8971***	–	3.4304
Pulse	−0.0580	0.9321***	2.8059***	0.0093*	−0.6262**	−1.2717**	3.4539

*significant at 10% level; **significant at 5% level; ***Significant at 1% level.
[1]See equation (1) in the text.
[2]See equation (3) in the text for "no dummy" and equation (4) for step or pulse dummies.
[3]See equation (5) in the text.

Figure 3 shows the FCE "pulse dummy" model from Table IV, showing the temporary increase in variability from adoption of SRI in March 1996 until January 2000 (the shaded area), followed by decline to around pre-SRI levels.

Figures 4 and 5 illustrating conditional standard deviation for the SUG and IUG "no dummy" models show a general decline in variability over the entire period, but it is clear that the March-96 to January-2000 SRI period (shaded) that is significant

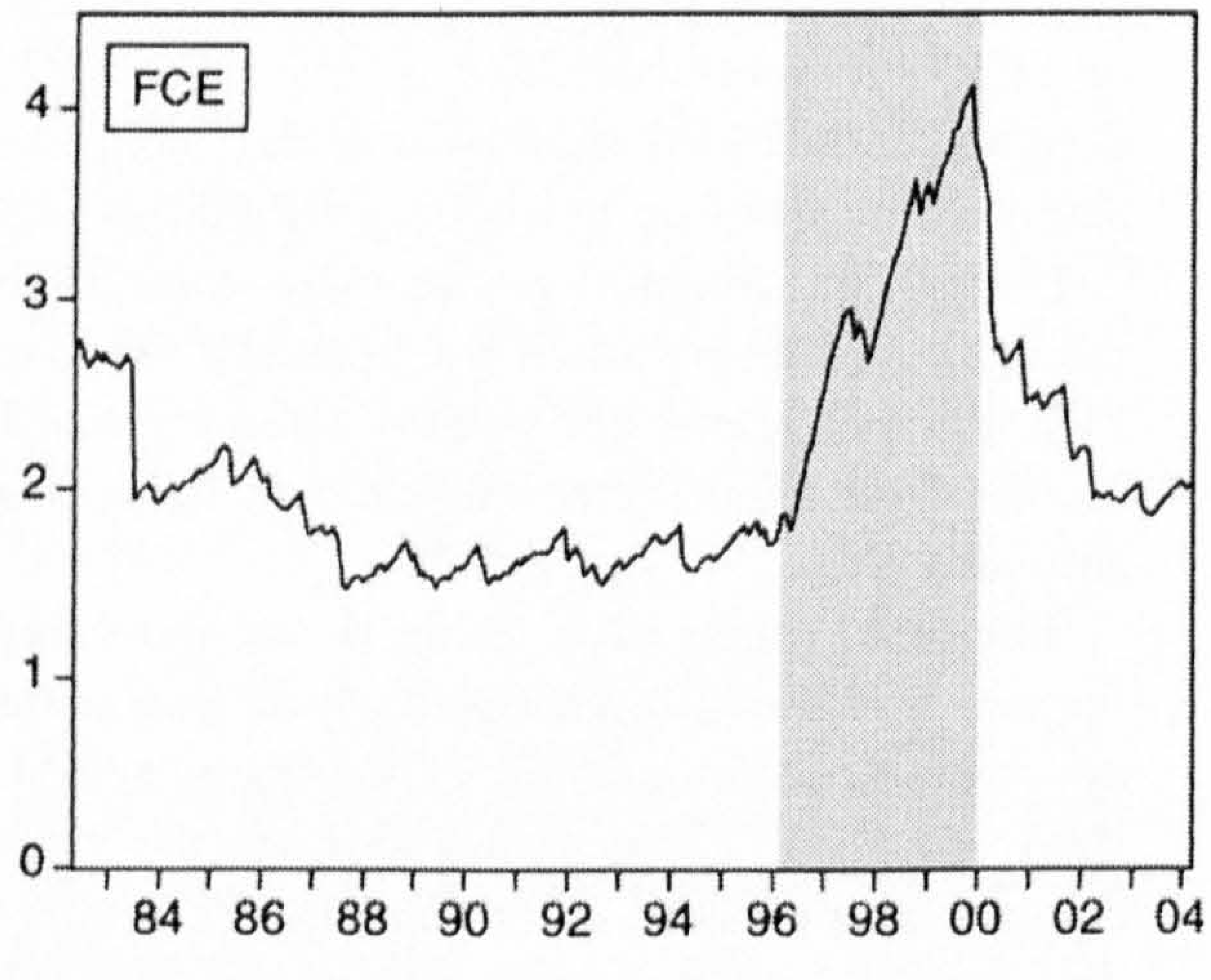

Figure 3. Conditional standard deviation of SRI fund FCE (% per month).

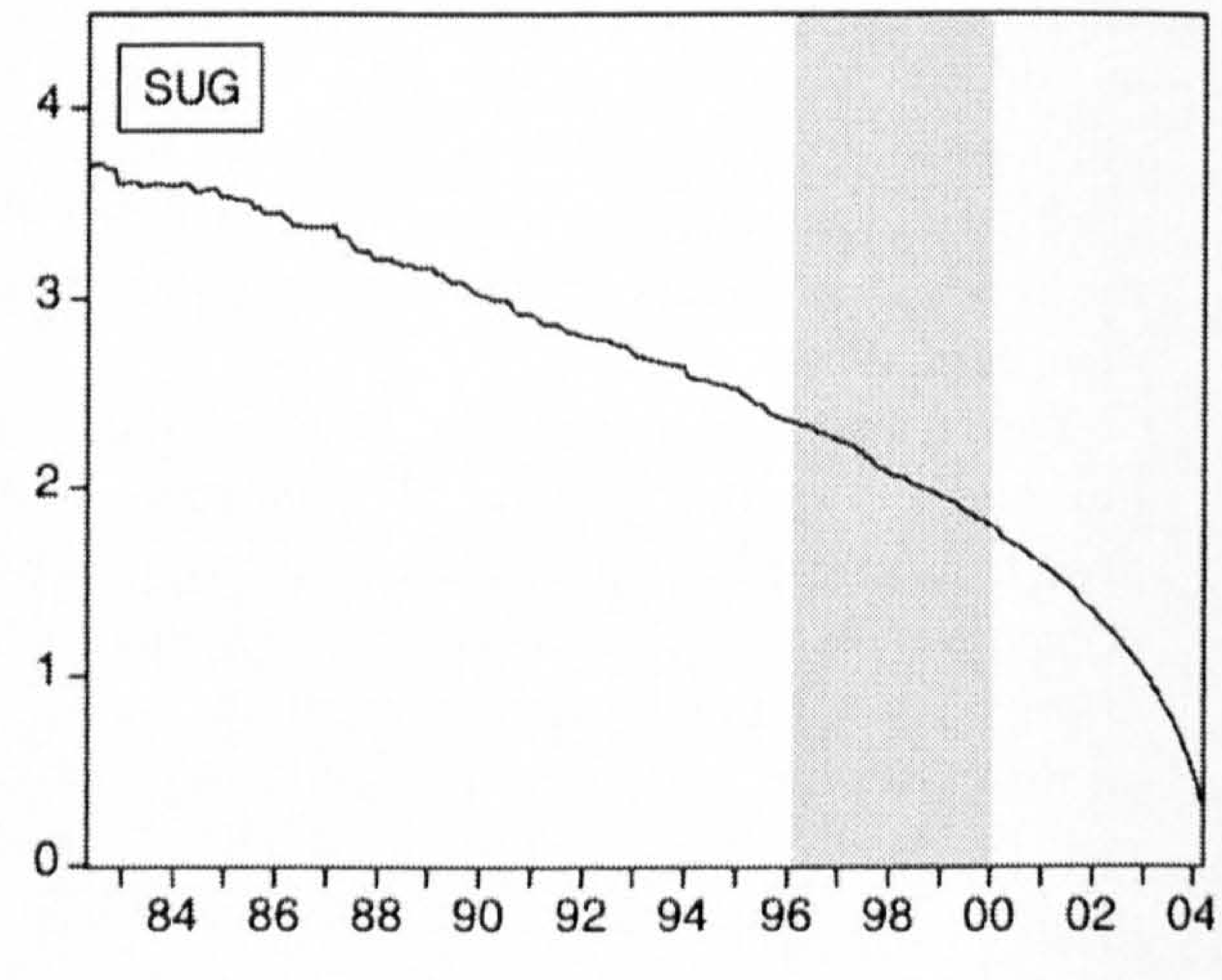

Figure 4. Conditional standard deviation of control SUG (% per month).

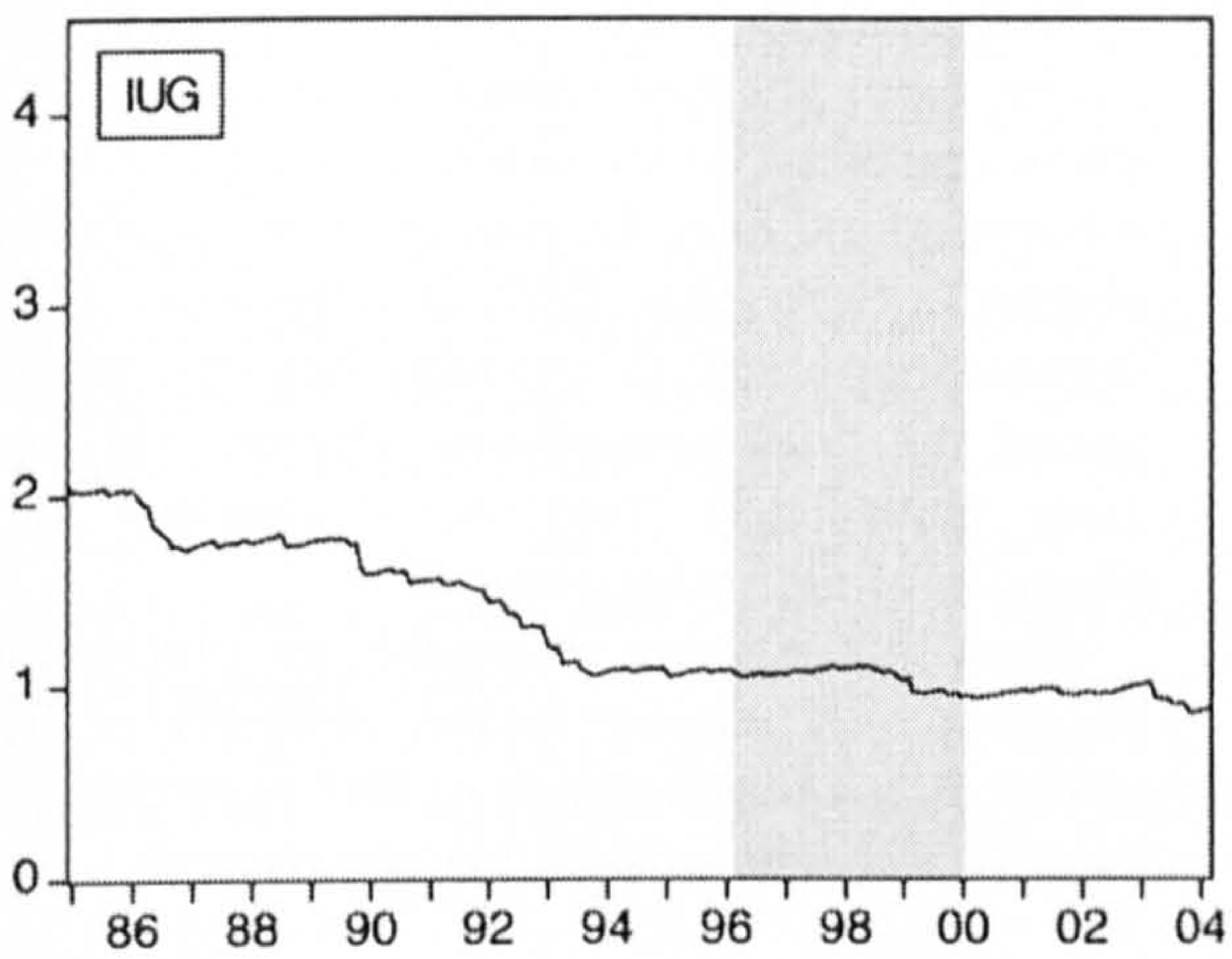

Figure 5. Conditional standard deviation of control IUG (% per month).

for SRI fund FCE has no particular significance for these two controls.

Figure 6 for MCI sheds further light on Table IV. Recall that in Table IV, the "pulse dummy" model was not rejected as firmly for MCI as for SUG and IUG. Although the lower SIC of 3.4304 indicates that the "no dummy" model is preferable, the MCI "pulse dummy" coefficient of −1.2717 is quite large and is statistically significant at the 5% level. In Figure 6 it can be seen that the SRI dummy partly captures a dip in conditional standard deviation that begins in 1993, considerably before March-96. Since this effect is over a different time period and in the opposite direction to the increase in FCE's variability, the conclusion that it is unrelated to the FCE effect seems warranted.

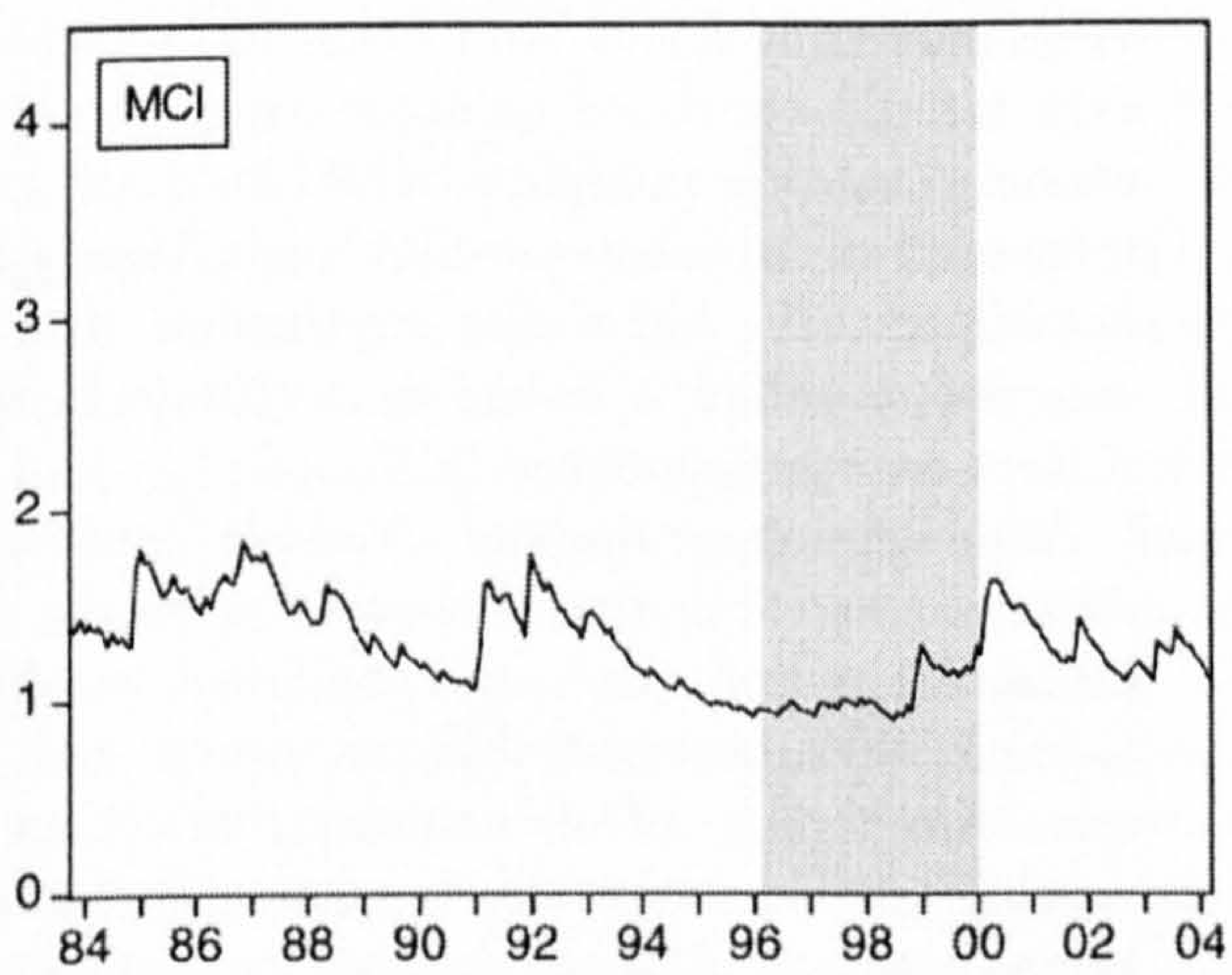

Figure 6. Conditional standard deviation of control MCI (% per month).

SRI effect or management change effect?

The results above support the view that the observed temporary increase in the variability of FCE's returns is due to a cause originating within FCE rather than a sectoral or market-wide effect. However, of course, adoption of SRI principles is not the only change within FCE that might influence fund performance. Perhaps a more likely source is a change in the way the fund is managed.

Information on changes in FCE management was provided by Brendan Vaughan, Investment Fund Accountant with Family Assurance Friendly Society since August 1996:

> In [September] 1997, Family Assurance launched Pavilion Asset Management, a wholly owned subsidiary company employing all of the former investment department and bringing in some new fund managers..." (Vaughan 2004, pers. commun.).

Information on management changes in the control funds was not available. It is hoped that the use of three control funds as opposed to the "matched pair" approach adopted by previous researchers makes it unlikely that all three control funds underwent similar confounding management changes over the relevant period of time.

It may be that the increase in FCE's variance began 18 months later, in September 1997, rather than in March 1996 at the time of SRI adoption. With this in mind the analysis was repeated with a "management" dummy regressor variable to discover whether this provides a better or worse fit to the data than a SRI dummy variable. The GARCH(1,1) model in equation (4) becomes:

$$\sigma_t^2 = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \gamma_{\text{man}}D_t^{\text{M}} + \delta\sigma_{t-1}^2 \qquad (6)$$

This is essentially the same as equation (4) only now SRI dummy D^{S}_t is replaced by management dummy D^{M}_t. The two variables differ with respect to start date, with management dummy D^{M}_t assigned a value of 1 from September-97 onwards (and 0 prior to this) whereas D^S_t is assigned a value of 1 from March-96 onwards. The end date of these "pulse dummies" can be varied so as to best fit the data.

The procedure by which the SIC was used to find the "best" SRI pulse dummy end date by varying the end date and selecting the specification with minimum SIC is now adapted to compare how well the SRI dummy and management dummy models fit the data.

In Figure 7, the solid line shows the SIC for every SRI dummy specification starting at March 1996 with a duration of first 6 months, then 7, then 8 months, and so on until the end of the data. As described above, SIC is minimum for an SRI dummy that is equal to 1 from March-96 until January 2000 and zero elsewhere, and this can be seen clearly in Figure 7.

The broken line in Figure 7 shows the SIC for every possible management dummy specification with a duration of 6 months or more. Two features are notable. First, there is no management dummy specification with a lower SIC than the best SRI dummy specification (and indeed management dummy SIC is almost always greater then SRI dummy SIC). Second, all of the lower management dummy SIC values occur before January 2000, suggesting that the relatively better fit of these management dummy models is due to partially "picking up" the later stages of a temporary SRI effect occurring between March-96 and January 2000.

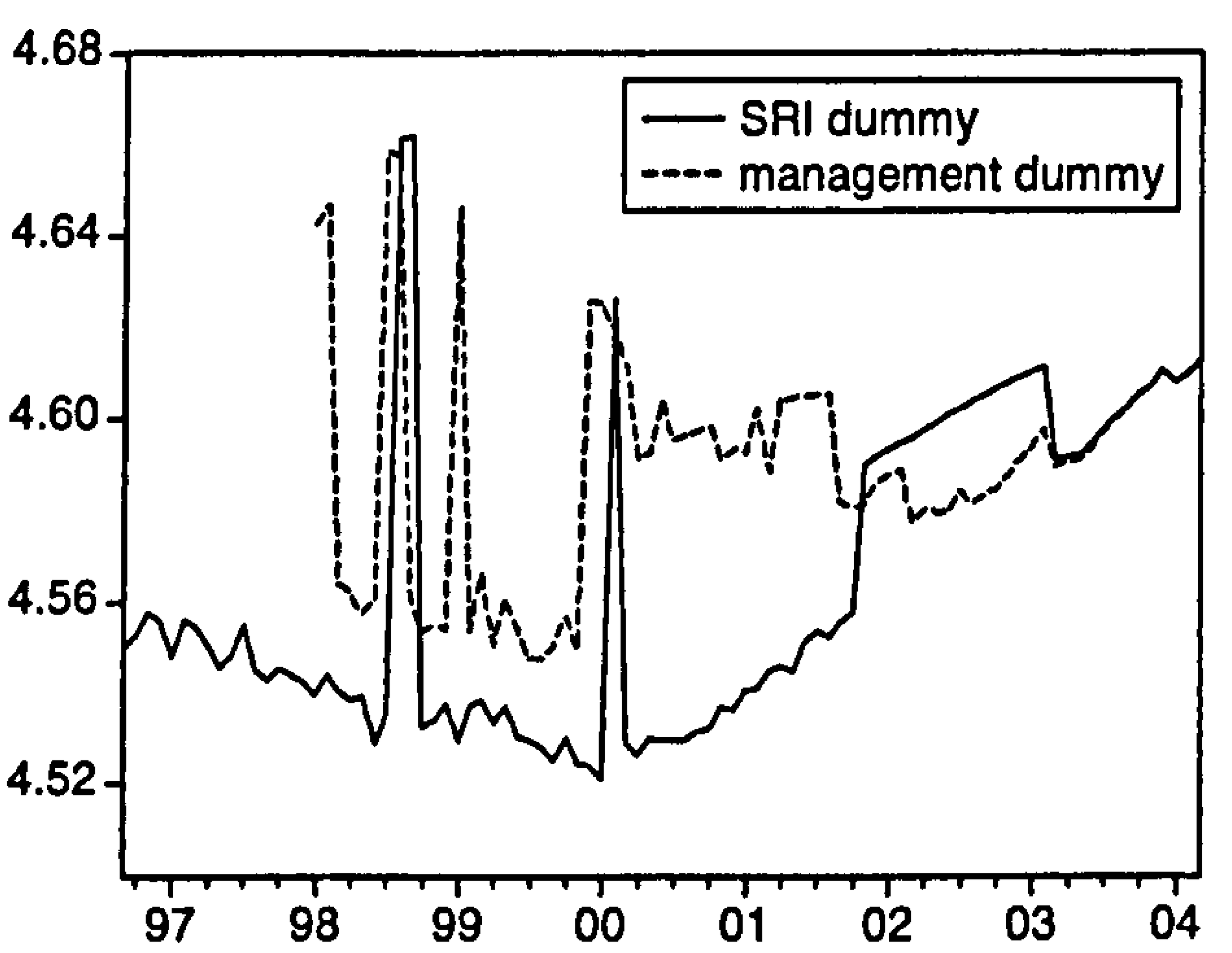

Figure 7. Schwarz information criterion (SIC) for SRI and management dummy variables of varying durations.

At this point it is also useful to return to Figure 1. In this figure the first vertical broken line indicates the timing of the switch to SRI in March 1996 while the second indicates the timing of the management change in September 1997. It is apparent that the increased turnover in portfolio holdings occurred before the fund management change, but in the years immediately prior and subsequent to the adoption of SRI principles.

From this it seems reasonable to conclude that the temporary increase in the variability of FCE's returns is due to the switch to SRI principles rather than to a change in fund management.

Conclusion

FCE has provided an unusual opportunity to investigate the effect of a switch from conventional investment objectives to SRI objectives, since most funds do not change investment objectives, remaining either "conventional" or "SRI" from date of launch.

Similarly to previous studies, no evidence has been found linking adoption of SRI with a change for better or worse in mean risk-adjusted return ("alpha", α_p). On this performance measure FCE appears to share with the control funds an ability to match, but not to exceed, the performance of the market index both before and after adoption of SRI.

The variability of SRI fund returns has been investigated rather little in previous studies, but here yields interesting results. An increase in variability of FCE returns was found to occur over a period of almost 4 years from adoption of SRI in March 1996, followed by a decline to pre-SRI levels. The data do not support the alternative explanation that the increased volatility is linked to a change in fund management in September 1997.

Although the dummy variable technique employed here can discriminate between the two explanations for the increase in variability (because they occur at different times) and enables the timing of the subsequent decline in variability to be estimated, it cannot discriminate between two alternative phenomena occurring at the same time. Thus to determine the cause of the decline in volatility from January 2000 is beyond the scope of the present study. Nonetheless some further comment on this topic may be of interest.

Seeking to relate the evidence above to the experience of fund managers, the views of the fund management company were sought. Brendan Vaughan, Investment Fund Accountant with Family Assurance Friendly Society since August 1996, provides the following useful comment, suggesting an intriguing possibility[4]:

> ...when Family Assurance introduced the ethical criteria to Family Charities Trust in 1996 ethical awareness and monitoring was a lot less common than it is now. At the time, the majority of investors had not heard of SRI and many had no idea of how the portfolio of their chosen investment vehicle was made up. The media attention spawned by the dot-com boom of the late 1990s along with the ability to access global information via the internet has led to the average investor being much more discerning and knowledgeable than their counterparts ten years ago. When this is also coupled with the fact that many multinational companies are now changing their strategies in their desire to be seen as "friendly" and "socially responsible" in a way that was not previously considered important in the corporate world then *the possible portfolios available to ethical funds and unit trusts is constantly expanding*. This allows the fund manager to pick the best stocks from a significantly wider range than previously available and accordingly *produce reasonable returns without exposing the fund to increased risk*. (Vaughan, 2004, pers. commun., emphasis added)

Vaughan is proposing that the post-January-2000 reduction in FCE's variability (following a period of increased post-SRI variability from March 1996) may be evidence of a link between the more widespread adoption of CSR by firms, and the financial performance of SRI funds such as FCE that seek to invest in socially responsible firms. Such interaction between CSR and SRI is quite different from the more commonly discussed influence of SRI in encouraging wider adoption of CSR. Indeed, the suggestion is that the more successfully CSR is encouraged, the better may be the financial performance of SRI funds. In the present case the evidence for such interaction is not strong, as it is not apparent that a large expansion in CSR activity occurred just prior to the drop in volatility from January 2000. However this may be an interesting direction for future research.

An alternative explanation with some intuitive appeal is "learning by doing": that is, post-SRI, fund managers could not at first reliably deliver similar financial performance, but with experience fund managers brought the volatility of returns back to previous levels. In the field of economics "learning by doing" in the sense of increasing labour productivity over time is long established, stemming from Arrow's seminal theoretical model (Arrow, 1962).

Regarding "learning by doing" by fund managers, FCE Investment Fund Accountant Vaughan commented as follows:

> I have no doubt that this is at least partly true although it is probably not the primary reason that the variability of returns improved. With any change to a business practice it takes time to adjust and as people become more confident and experienced in any discipline, you would expect their relative performance to improve. The fund manager structure used by Family Assurance has however changed significantly since 1996... there has not been an individual responsible for the management of the Family Charities Trust from 1996 to the present time. In fact none of the original fund management team remain. It is therefore impossible to state definitively that the skills of individual managers improved... (Vaughan, 2004, pers. commun.).

The complete change of personnel referred to by Vaughan occurred due to management changes in 2001 and 2003 (sale of Pavilion Asset Management to Seymour Pierce in two stages) and 2004 (management passed to New Star Asset Management), whereas the 1997 launch of Pavilion Asset Management continued to employ "all of the former investment department" (see above). Thus there does appear to have been continuity of personnel prior to and somewhat after January 2000 (when the decline in volatility occurred). Thus learning by fund managers cannot be ruled out in this case.

FCE has provided a useful opportunity to examine the financial performance of an SRI fund in a novel way and suggests some directions for future research. There appears to be little published evidence comparing the variability of SRI and non-SRI funds, suggesting that wider investigation may be fruitful. Interesting unanswered questions have also been raised. Future empirical work might explore in detail a possible link between SRI performance and the spread of CSR activity, taking account of particular CSR events or initiatives that may facilitate the practice of SRI, or making use of appropriate measures of the extent of CSR activity. And the possibility of a relationship between fund manager learning by doing and improved financial performance over time would seem to apply to any novel investment strategy, not merely to SRI, and so to have potentially wide application.

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Notes

[1] The results in Table III proved robust to some refinements, that is, the "timing" of Fama (1972) implemented using both the dummy variable model of Henriksson and Merton (1981) and also the quadratic Treynor and Mazuy (1966)/Bhattacharya and Pfleiderer (1983) model. Use of White's (1980) heteroscedasticity consistent standard errors did not materially affect the results.

[2] Variations on ARCH models were also explored, such as the Threshold ARCH of Zakoian (1990) and Glosten et al. (1993), Engle et al.'s (1987) ARCH-in-Mean model, Nelson's (1991) exponential GARCH plus transitory and permanent component models. The GARCH(1,1) model did indeed prove to be sufficient.

[3] The Akaike information criterion (Akaike 1974) was also considered, and gave the same results.

[4] Brendan Vaughan wishes to make it clear that his views (other than those relating to matters of fact concerning FCE) are based on opinion and experience rather than on a full, systematic investigation and analysis.

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